The University of Adelaide
Faculty of the Professions
School of Economics

Essays on Political Economy and Economic Development

a thesis

by

Dessie Tarko Ambaw

submitted in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

September, 2018

Table of Contents

List of Tables

List of Figures

Abstract

This thesis explores the causal effect of institutional, geographical and cultural factors on civil conflict and economic development in developing countries. It contains an introduction to the thesis, followed by six self-contained papers, and a concluding chapter that summarizes the main findings of the thesis. The thesis begins by exploring the effect of economic factors on the likelihood of civil conflict in sub-Saharan Africa (SSA). Particularly, Chapter 2 investigates the causal effect of economic policy shocks that are related to the real exchange rate (RER) misalignment on civil conflict in SSA. To address the potential endogeneity problem, the chapter implements two stage least square (2SLS) and GMM estimation and finds that RER overvaluation significantly raises the likelihood of conflict in the region. Chapter 3 studies the effect of emergency food aid on the incidence of civil conflict in SSA. This study proposes a novel identification strategy (IV) to isolate the causal effect of emergency food aid on conflict. Unlike the previous literature, I do not find a statistically significant impact of food aid in raising civil conflict.

The next three chapters focus on identifying the effect of the introduction of monetary policy rules, geographical impediment and agricultural market institution on economic integration in the form of FDI, export and import flows. More specifically, Chapter 4 compares the effectiveness of inflation targeting and fixed exchange rate monetary policy rules in attracting FDI in the context of developing countries. Using propensity score and difference-in-differences estimation techniques, we find that the two monetary policy rules are equally important in increasing the inflow of FDI to these countries. Chapter 5 investigates the causal effect of landlockedness on disaggregate export and import. Exploiting the *de facto* landlockedness of Ethiopia in 1998 and using a triple-differencing strategy, we find that landlockedness has a large negative and statistically significant effect on the import and export of several goods in Ethiopia. Chapter 6 examines the introduction

of a modern agricultural commodity market institution in Ethiopia on the export of coffee, the major export item in the country. Using the establishment of the Ethiopian Commodity Exchange (ECX) in 2008 and the sudden introduction of coffee into the ECX platform, it implements a triple difference-in-differences estimation approach and shows that the export of coffee has significantly improved following the introduction of coffee trade through the ECX.

Finally, Chapter 7 explores the role of deep-rooted historical factors on the diffusion of technology from the technology frontier to laggard countries. This chapter has two major contributions to the literature. Firstly, it provides a micro channel evidence through which genealogical distance reduces the diffusion of technology from the technology frontier. Secondly, it sheds light on the distributional impact of genetic distance on the productivity of firms. Employing a harmonized survey data and a novel group IV quantile approach, it finds that the effect of genetic distance tends to be stronger for firms that are more productive. Additionally, it shows that cultural barriers to the diffusion of technology across countries affect firm-level productivity through firms' ability to adopt technologies from the frontier countries.

Acknowledgements

There are several people that I am immensely grateful for their constant support and encouragement during the preparation of this PhD thesis. My first sincere gratitude goes to my principal supervisor Dr. Nicholas Sim for his excellent supervision and guidance throughout the three years period. I was greatly benefited from his constructive comments, continuous encouragement and from his vast knowledge in multiple areas of economics. I would also like to thank my co-supervisor Dr. Firmin Doko Tchatoka for his kind support and inspiration throughout this important journey. I am very delighted to extend my heartfelt appreciation to my co-supervisor Dr. Terence Cheng for his ongoing advice in writing this thesis and for encouraging me to exploit my potential to the fullest during the entire study period.

Next, I would like to express my sincere acknowledgement to my friend and co-author Habtamu Tesfaye Edjigu for the several helpful discussions and advice during my study. My special thanks also goes to Dr. Nadya Baryshnikova, Dr. Stephanie McWhinnie, Associate professor Shandre Thangavelu, Dr. Ngoc Pham, Associate Professor Paul Pezanis-Christou, Professor Gareth Myles, Dr. Benedikt Heid and Dr. Yohannes Ayele for their invaluable suggestions and comments in the preparation of this dissertation. My profound thanks goes to all the School of Economics staffs and fellow postgraduate students for making may stay enjoyable. I gratefully acknowledge financial support from the University of Adelaide.

Finally, I express my deepest gratitude to my family for their endless love, continuous support and encouragement during the entire journey of my study.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

The author acknowledges that copyright of published works contained within this thesis resides with the copyright holder(s) of those works.

I also give permission for the digital version of my thesis to be made available on the web, via the Universitys digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

Dessie Tarko Ambaw

SIGNATURE .... DATE ....

Dedication

To My DAUGHTER

Chapter 1

Introduction

There is a large difference in economic development across countries. For example, the average income per capita level between the world's advanced and poorest countries differs by a factor of more than 100 (Rodrik et al., 2004). What accounts this large differences in economic development across countries and how can we reduce it? This is one of the most challenging questions in the development economics literature over the past four decades (Hall and Jones, 1999; Spolaore and Wacziarg, 2013). Scholars have offered different explanations for the stark divergence on the level of economic development between the rich and the poor countries. Among the several candidate explanations three fundamental determinants stand out in the literature (Easterly and Levine, 1997; Collier and Gunning, 1999; Rodrik et al., 2004).

The first underlying cause behind the sluggish economic performance of developing countries is poor geography. Geography is regarded as a fundamental determinant of economic development as it strongly influence climate, disease burden, endowment of natural resources, transport costs, and the diffusion of knowledge and technology from the developed countries (Rodrik et al., 2004). The second fundamental or "deeper" determinant of economic development is the establishment of good institutions. Institutions refer to the rules, regulations, laws and policies that affect economic incentives (Acemoglu, 2008). A high quality institutional environment enables the government to design as well as adopt appropriate economic policies, incentivize individuals to undertake more productive socio-economic activities, and increase the effectiveness of international aid (World Bank, 2014). The third core determinant of development is culture which refers to beliefs, values and preferences of an individual or a society that influence economic behavior.

Moreover, civil conflict is regarded as one of the leading causes of human suffering and underdevelopment in developing countries (Eck and Hultman, 2007; Abadie and Gardeazabal, 2003; Collier, 2008). Fore instance, conservative estimates suggest that around 16.2 million deaths occurred in 127 civil wars between 1945 and 1999 (Fearon and Laitin, 2003). What are the underlying root causes of the prevalence of civil conflict in these countries? Anthropologists and political scientists have studied this topic for several decades. The former group tend to focus on longstanding ethnic and religious hatreds as the primary causes of conflict. But, political scientists who are on the political right group claim lack of democracy as the central cause of conflict. They argue that violence occurs when opportunities for the peaceful resolution of political disputes are scarce. On the contrary, political scientists on the political left side argues that the underlying causes of civil conflict are economic inequalities and the deep-rooted legacy of colonialism (Collier et al., 2003; Collier, 2008). Very recently, economists start to conduct thorough empirical studies to better understand the causes of civil conflict and war. They provide evidence that civil conflict is more likely to occur in poor countries that are prone to negative income shocks, have weak institutions, sparsely populated peripheral regions, and mountainous terrain. Yet, the most robust empirical finding in the economic literature is that the likelihood of civil war is strongly correlated with lower per capita income (Blattman and Miguel, 2010). As such, high incidence of civil war and poor economic performance are the two intertwined core economic development challenges of least developing countries.

Despite the success of the literature on identifying the root causes of economic development and the likelihood of civil war, providing compelling explanations using more credible econometric methods that establish causality has become a new and most promising avenue of empirical research (Easterly and Levine, 1997; Rodrik et al., 2004; Blattman and Miguel, 2010; World Bank, 2014). This thesis explores the impact of different factors that impede economic development via influencing international economic integration between advanced and least developing countries (LDCs). In particular, the thesis consists of six self-contained chapters that explore the causal impact of economic policy, institutional, geographical and cultural factors on the probability of civil conflict and economic development in the context of LDCs.

Chapter two investigates the effect of income reducing shocks on civil conflict in SSAs (*sub-Saharan African countries* in short). Here, we demonstrate that a new type of economic shock, which is related to the misalignment of the real exchange rate (or RER, interchangeably), can explain civil conflict beyond the effects of rainfall and commodity price shocks. Why would the real exchange rate matter for the SSAs? For developing countries, especially the SSAs, RER misalignment is a common empirical phenomenon (Ghura and Grennes, 1993; Elbadawi et al., 2012). Besides, the export industry is an important driver of growth for developing countries (Krueger, 1998 for example). This is particularly true for the SSAs where the export sector accounts for more than a third of GDP (Deaton et al., 1995; Deaton, 1999; Elbadawi et al., 2012). Because of their reliance on exports, the SSAs are vulnerable to RER shocks, especially those leading to an RER overvaluation, as it erodes the comparative advantage of the exporting industry and acts as an implicit tax on exporters (Ghura and Grennes, 1993), which potentially results in the loss of income and therefore an increased risk of conflict.

Our estimated results show that RER misalignment is statistically significant for the incidence of civil conflict in the SSAs, where a one-standard-deviation increase (i.e. overvaluation) in the real exchange rate is associated with a 4% increase in civil conflict incidence on average. This effect is present even after controlling for rainfall and commodity price shocks – two widely acknowledged factors of civil conflict. Hence, RER misalignment has explanatory power on civil conflict in the SSAs beyond what rainfall and commodity price shocks may explain. Furthermore, when we decompose the misalignment index into RER over and undervaluations, we find that only RER overvaluations are statistically significant for civil conflict. Thus, the effect of RER misalignment on conflict is driven mainly by the effect of RER overvaluation. Our work has policy implications, as it suggests that beyond having economic benefits, the stabilization of the real exchange rate may foster political stability in SSA by helping to reduce conflict in the region.

The third chapter extends our analysis on the determinants of economic factors on civil conflict. In this chapter, we investigate the impact of emergency food aid on the incidence of civil conflict. In the foreign aid literature, finding a convincing instrumental variable in order to identify its effect on civil conflict and economic growth is problematic (Galiani et al., 2017). To address the potential endogeneity problem in the food aid vis-a-vis civil conflict relation, I propose a new instrumental variable. Here, I employ the number of natural disaster affected people in other SSA countries as an instrumental variable to emergency food aid. The two stage least square (2SLS) estimates suggest that emergency food aid has no a statistically significant effect in increasing civil conflict in SSA countries. In addition, I generate and control the first order and the second order spatial lagged conflict variables to consider the spatial spillover effect of civil conflict in SSA. Despite the existence of large civil conflict spillover in SSA, we fail to find a statistically significant effect of food aid on conflict. As such, food aid can still be used as an important international development policy tool to fight hunger and suffering in developing countries.

International integration is a fundamental determinant for economic development (Rodrik et al., 2004). For example, it has a large role in fostering the economic convergence between the advanced and the poor countries of the world. Factors such as economic policy uncertainty, landlockedness, poor institutional quality and cultural factor may, however, impede international economic integration between countries. The rest of the thesis examines the impact of these factors on the flow of trade, foreign direct investment (FDI) and technology to developing countries. In particular, in chapter four we compare the effect of inflation targeting (IT) and fixed exchange rate monetary policy regimes in attracting in FDI in a context of developing countries. To address the endogeneity problem that may arise due to the self selection problem of the monetary policy rules, we employ difference-in-differences (DiD) and propensity score matching estimation (PSM) techniques.The findings show that the two monetary policy rules are equally effective in attracting FDI.

Chapter five extends the analysis on international market integration and its determinant factors. The chapter investigates the causal effect of landlockedness on the trade flow. To quantify the impact of landlockedness, existing studies typically rely on a time invariant dummy variable – an indicator of landlockedness - that takes a value of one if a country is landlocked and zero otherwise. However, the country fixed effect will partial out the time invariant landlocked indicator, causing the effect of landlockedness to be unidentified. Moreover, there is no empirical evidence that examines whether the impact of landlockedness is temporal or long-lasting. This chapter provides the first natural experiment that explores the causal effect of landlockedness on trade using the sudden "*de-facto*" landlockedness of Ethiopia in 1998. In doing so, we address two empirical issues that have constrained existing studies. First, there is a general lack of data on time varying trade barrier measurements. Second, researchers confront identification issues while comparing trade shares between coastal and landlocked countries as trade itself may affect trade cost. Hence, the presence of reverse causality may result biased conclusions.

Our main estimation technique that is employed to identify the causal impact of landlockedness is the triple-differencing (DDD) approach. This approach exploits three sources of variation: country variation (landlocked country–Ethiopia– and coastal country–Kenya), product variation (bulky ocean-borne freight and light airborne freight) and time variation (before and after "*de facto*" landlockedness). We find that landlockedness has a large negative impact on Ethiopia's export and import products.The results show that landlockedness on average reduces the export of coffee, leather, crude vegetable and hide & skin by about 43%, 49%, 80% and 72%, respectively. In addition, landlockedness has a strong negative effect on different ocean-borne imported goods of Ethiopia. For example, landlockedness reduces the import of petroleum, fuel and fertilizer by 71%, 68.6% and 66.9%, respectively. For a developing economy that highly depends on agriculture a 68.6% reduction in fertilizer import, for instance, has an important implication on the productivity of the sector.

Chapter six extends the analysis on the establishment of modern market institution and trade flows. Agricultural commodity exchanges help to eliminate exploitative intermediaries, provide more transparency on the prevailing market price to producers, and ultimately, promote agricultural production and exports. So far, there were no empirical evidences that analyze the impact of agricultural commodity exchanges on export in the context of developing countries. By exploiting the introduction of the Ethiopia Commodity Exchange (ECX) in 2008 as a quasi-natural experiment, this chapter examines effect of the ECX on coffee export in Ethiopia. To minimize some of the criticisms of the gravity literature, we include a full set of country pair, exporter-year, exporter-product, product-year, and importer-year fixed effects. The estimated results show that the ECX has a large positive impact on the country's coffee export. Our main results show that ECX has increased coffee export on average by about 84%. In addition, the ECX has a statistically significant impact on new market destinations (i.e. the extensive margin of coffee export increases).

The diffusion of technology from advanced to poor countries is another crucial factor for economic convergence between them. The last chapter explores the role of deep-rooted historical factors on the diffusion of technology from the technology frontier to laggard countries. This chapter has two major contributions to the literature. First, it provides micro channel evidence through which genealogical distance reduces the diffusion of technology from the technology frontier to the adopter countries. Second, we investigate the distributional impact of genetic distance on the productivity of firms. Employing the survey data of more than 32,000 firms and a novel group quantile instrumental variable (GQIV) estimator, we find that the effect of genetic distance is bigger for high productive firms. The findings provide an underlying mechanism for the earlier empirical studies in such a way that cultural differences reduce the flow of technology to firms (which reduce firm productivity) and hence the diffusion of development for the country.

The reminder of the thesis is structured as follows. Chapter 2 provides the analysis that investigates the causal effect of RER shocks on civil conflict in SSA. Chapter 3 shows the causal effect of emergency food aid on civil conflict in SSA. Chapter 4 presents the causal effect of monetary policy regimes on FDI in the context of developing countries. Chapter 5 and 6 considers how landlockedness and agricultural commodity exchange affect export and import flows in Ethiopia. Finally, chapter 7 provides the distributional effect of cultural and deep-rooted historical factors on the diffusion of technology in developing countries.

References

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque Country. *The American Economic Review 93*(1), 113–132.

Acemoglu, D. (2008). *Introduction to modern economic growth.* Princeton University Press.

Blattman, C. and E. Miguel (2010). Civil war. *Journal of Economic Literature 48*(1), 3–57.

Collier, P. (2008). *The bottom billion: Why the poorest countries are failing and what can be done about it.* Oxford University Press, USA.

Collier, P. et al. (2003). *Breaking the conflict trap: Civil war and development policy.* World Bank Publications.

Collier, P. and J. W. Gunning (1999). Why has Africa grown slowly? *Journal of Economic Perspectives 13*(3), 3–22.

Deaton, A. (1999). Commodity prices and growth in Africa. *The Journal of Economic Perspectives 13*(3), 23–40.

Deaton, A., R. I. Miller, et al. (1995). *International commodity prices, macroeconomic performance, and politics in Sub-Saharan Africa.* International Finance Section, Department of Economics, Princeton University.

Easterly, W. and R. Levine (1997). Africa's growth tragedy: policies and ethnic divisions. *The Quarterly Journal of Economics 112*(4), 1203–1250.

Eck, K. and L. Hultman (2007). One-sided violence against civilians in war: Insights from new fatality data. *Journal of Peace Research 44*(2), 233–246.

Elbadawi, I. A., L. Kaltani, and R. Soto (2012). Aid, real exchange rate misalignment, and economic growth in sub-Saharan Africa. *World Development 40*(4), 681–700.

Fearon, J. D. and D. D. Laitin (2003). Ethnicity, insurgency, and civil war. *American Political Science Review 97*(1), 75–90.

Galiani, S., S. Knack, L. Xu, and B. Zou (2017). The effect of aid on growth: evidence from a quasi-experiment. *Journal of Economic Growth 22*(1).

Ghura, D. and T. J. Grennes (1993). The real exchange rate and macroeconomic performance in sub-Saharan Africa. *Journal of Development Economics 42*(1), 155–174.

Hall, R. E. and C. I. Jones (1999). Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics 114*(1), 83–116.

Krueger, A. (1998). Why trade liberalization is good for growth. *The Economic Journal 108*(450), 1513–1522.

Rodrik, D., A. Subramanian, and F. Trebbi (2004). Institutions rule: the primacy of institutions over geography and integration in economic development. *Journal of Economic Growth 9*(2), 131–165.

Spolaore, E. and R. Wacziarg (2013). How deep are the roots of economic development? *Journal of Economic Literature 51*(2), 325–69.

World Bank (2014). The development economics of landlockedness: Understanding the development costs of being landlocked. Technical report.

Chapter 2

Economic Shocks and Civil Conflict in sub-Saharan Africa: New Evidence from Real Exchange Rate Misalignment

Dessie Tarko Ambaw[a] Nicholas Sim[a,b]

[a]*School of Economics, The University of Adelaide*

[b]*School of Business, The Singapore University of Social Sciences*

Statement of Authorship

Title of Paper	Economic Shocks and Civil Conflict in Sub-Saharan Africa: New Evidence from Real Exchange Rate Misalignment
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
Publication Details	The paper is written in publication style for submission to a journal.

Principal Author

Name of Principal Author (Candidate)	Dessie Tarko Ambaw		
Contribution to the Paper	Contributed to initiating the research idea, planning the article and the methodology, conducted the literature review, collected the data, analysed and interpreted the results, wrote part of the manuscript and acted as the corresponding author.		
Overall percentage (%)	75%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	06/09/2018

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Nicholas Sim		
Contribution to the Paper	Contributed to the planning of the article, supervised the development of the work, helped in the interpretation of the results and wrote part of the manuscript.		
Signature		Date	06/09/2018

Abstract

Real exchange rate (RER) misalignment, which is the deviation of the actual real exchange rate from its equilibrium, occurs frequently in developing countries. In this paper, we show that civil conflict in sub-Saharan Africa can be influenced by RER misalignment. To do so, we construct an RER misalignment index whose variation is driven by shocks to each country's RER fundamentals. Based on a panel of 35 countries from 1975 to 2006, we find that RER misalignment has a statistically significant effect of increasing the incidence of civil conflict in sub-Saharan Africa. Crucially, this effect is present even when rainfall and commodity price shocks – two widely acknowledged factors of civil conflict in the region – are controlled for. Thus, the stabilization of the real exchange rate may foster political stability in sub-Saharan Africa by having preventive effects on conflict in the region.

Key Words: Civil Conflict, Real Exchange Rate Misalignment, Economic Shocks, sub-Saharan Africa

JEL Codes: D74, E32, F31, F41, O11

2.1 Introduction

One of the leading causes of human suffering and underdevelopment in sub-Saharan Africa is civil conflict (Eck and Hultman, 2007; Abadie and Gardeazabal, 2003; Collier, 2008). In the last two decades, researchers have shown that economic related determinants may affect civil conflict primarily by causing income to decline. The idea is that income is negatively associated with civil conflict, possibly through the opportunity cost hypothesis where individuals are more willing to fight if their income is low (Collier and Hoeffler, 1998; Grossman, 1991), or the state capacity hypothesis where low income countries have limited state revenue to combat insurgency and thus reduce conflict. As such, civil conflict may arise from income reducing shocks, such as negative rainfall shocks as shown by Miguel et al. (2004), Burke et al. (2009), and Ciccone (2013), or negative commodity price shocks as shown by Brückner and Ciccone (2010) for sub-Saharan Africa.

For the SSAs (*sub-Saharan African countries* in short), we demonstrate that a new type of economic shock, which is related to the misalignment of the real exchange rate (or RER, interchangeably), can explain civil conflict beyond the effects of rainfall and commodity price shocks. Why would the real exchange rate matter for the SSAs? One reason is due to the fact that the export industry is an important driver of growth for developing countries (see, for example Krueger, 1998). For the SSAs, the export sector accounts for more than a third of their GDP (Deaton et al., 1995; Deaton, 1999; Elbadawi et al., 2012).[1] Because of their reliance on exports, the SSAs are vulnerable to RER shocks, especially those that lead to an RER overvaluation, as this will erode the comparative advantage of the exporting industry and acts as an implicit tax on exporters (Ghura and Grennes, 1993). As such, these shocks could lead to a loss of income and therefore heighten the risk of conflict.

The misalignment of the real exchange rate, which is common in the SSAs (Ghura and Grennes, 1993; Elbadawi et al., 2012), is the deviation of the observed real

[1]Figure (2.4) in Appendix D which presents the time series plots of export as a percentage of GDP shows the contribution of the export sector to the SSA economy.

exchange rate from its equilibrium level.[2] To study the effects of RER misalignment on civil conflict, we build upon the vast international finance literature to construct an RER misalignment index (Edwards, 1989; Goldfajn and Valdes, 1999; Elbadawi et al., 2012). Based on a panel of 35 SSAs from 1975 to 2006, we find the following results.

Firstly, RER misalignment is statistically significant for civil conflict in the SSAs. In our baseline regression, we find that a one-standard deviation increase (i.e. overvaluation) in the real exchange rate is associated with a 4 percentage point increase in civil conflict incidence on average. Crucially, this effect is present even after controlling for rainfall and commodity price shocks – two widely acknowledged factors of civil conflict. Secondly, when we decompose the misalignment index into RER over and undervaluations, we find that only RER overvaluations are statistically significant for civil conflict, which suggests from a policy perspective that we should be cautious about RER overvaluation. Finally, we employ system Generalized Method of Moments (GMM) and instrumental variable regressions to address potential concerns about reverse causality. We still find that RER misalignment has explanatory power for civil conflict in the SSAs beyond the effects of rainfall and commodity price shocks. Importantly, the estimated effect sizes from the system GMM and IV regressions are even stronger, which suggests that our baseline estimates are conservative about the effect of RER misalignment on civil conflict. Hence, other than stabilizing the RER volatility, it is important for central banks to manage and ensure that RER is not overvalued.

Our paper is related to a well-established literature that investigates the effect of income shocks on civil conflict. There are two prominent strands of research in this area. The first, led by Miguel et al. (2004), Ciccone (2011), and Ciccone (2013) show that negative climate shocks may reduce agricultural income, and thus, increase the likelihood of civil conflict in the SSAs. The second, led by Brückner and Ciccone (2010), Savun and Cook (2010), Bazzi and Blattman (2014), and Janus and

[2]Simply put, the equilibrium real exchange rate is the exchange rate that results in the simultaneous attainment of equilibrium in the domestic (non-tradable goods) and external (current and capital account) sectors of the economy (e.g. Nurkse, 1945; Edwards, 1989).

Riera-Crichton (2015), use international commodity price shocks and terms of trade shocks as sources of exogenous variations in income. The idea is that the exports of the SSAs are usually not well diversified. As such, a fall in the international price of commodities, especially the ones the SSAs' export, may have large negative effects on their income (which would then increase the risk of civil conflict). Recently, there has been interest in whether non-traditional factors, such as exchange rate regimes (Hull and Imai, 2013), may explain civil conflict. Our paper contributes along this direction by examining if real exchange rate misalignment may explain civil conflict beyond traditional factors such as rainfall and commodity price shocks.

The rest of the paper is structured as follows. In Section 2.2, we provide some background on studies that have looked the effect of real exchange rate misalignment on economic growth and export in the SSAs. In Section 2.3, we discuss how our RER misalignment index is constructed. In Sections 2.4, 2.5 and 2.6, we discuss the data used, the estimating equation, and the estimation results. We offer some concluding remarks in Section 2.7.

2.2 Background on Real Exchange Rate Misalignment, Growth and Exports

2.2.1 Real Exchange Rate Misalignment and Economic Growth

The negative RER misalignment on the economic performance of developing countries are well-documented. In the literature, it has been found that developing countries have frequently experienced large deviations of their actual real exchange rates from their equilibrium levels (Ghura and Grennes, 1993; Elbadawi et al., 2012). Since RER misalignment may negatively affect economic growth, and thus income, RER misalignment could potentially affect civil conflict in the SSAs through the income mechanism.

Several empirical studies have explored the effect of RER misalignment on economic growth in developing countries. One of the earliest to do so is Cottani et al. (1990), who show that RER misalignment – in the form of overvaluation – may strongly and negatively affect economic growth in Asian, Latin American and African countries. Another early work is Ghura and Grennes (1993), who employ various measures of RER misalignment to demonstrate (for the SSAs) that the negative effect of misalignment on growth is a robust empirical phenomenon. More recently, Rodrik (2008) finds that the channel through which RER overvaluation reduces growth in developing countries comes mainly from the negative impact of overvalued currencies on the tradable sector.[3]

Other studies on RER misalignment include Elbadawi et al. (2012), who examine how RER misalignment affects economic growth and foreign aid received by the SSAs. They find that while RER overvaluation leads to lower growth on average, this negative effect is further exacerbated when a country receives more foreign aid. Finally, Schröder (2013) shows that by explicitly taking into account of the heterogeneity in how real exchange rates behave across countries (i.e. by estimating the misalignment of the real exchange rate for each country), he finds that not only may RER overvaluation reduce growth, it is possible for undervaluation to negatively affect growth as well.

2.2.2 Real Exchange Rate Misalignment and Exports

Why would RER misalignment negatively affect economic growth? One common argument is that RER misalignment, especially RER overvaluation, hinders the performance of the export sector in developing countries. One of the earliest evidence on the SSAs comes from Ghura and Grennes (1993), who show that RER overvaluation may reduce the amount of exports produced, as it acts as an implicit tax by reducing the profitability in producing exportable goods, both agricultural and non-agricultural. Pick and Vollrath (1994) estimate the effect of RER misalignment on the agricultural export sector performance in developing countries, and find this

[3] Rodrik (2008) shows that this relationship holds only for developing countries: the relationship disappears when the sample is restricted to developed countries. Thus, he concludes that avoiding RER misalignment can help to facilitate the economic convergence of developing countries with developed countries.

effect to be negative and statistically significant. Elbadawi et al. (1998) further demonstrate that the negative effect of RER misalignment is present even after controlling for RER volatility. Thus, the negative effects of RER misalignment on exports extend beyond the negative effects of RER volatility.

For developing countries, the negative effects of RER misalignment on exports are not limited to agricultural exports. Sekkat and Varoudakis (2000), for example, find that manufacturing exports from the SSAs may shrink when the real exchange rates of these countries become more overvalued. Similarly, Freund and Pierola (2012) find that in developing countries, surges in manufacturing exports, defined as "significant and sustained increase in export growth from one seven-year period to the next" (p. 387 in Freund and Pierola, 2012), are preceded by large RER undervaluations. Sekkat (2016) also finds that RER misalignment can affect export diversification in developing countries.

In short, there is evidence that RER misalignment, especially RER overvaluation, may negatively affect exports and growth. By reducing growth, RER misalignment could potentially increase civil conflict incidence in the SSAs, which is to be investigated here.

2.3 Deriving the Real Exchange Rate Misalignment Index

We follow the procedure in Elbadawi et al. (2012) to construct our RER misalignment index. Before going into details, we offer some intuition that underlies what the procedure entails. The actual procedure will be discussed in detail in Sections 2.3.1 through 2.3.3.

The real exchange rate is misaligned if the observed RER is not equal to the equilibrium RER. As such, we construct the RER misalignment index ($Misalignment_{it}$) by taking the difference between the observed RER (RER_{it}) and the equilibrium RER (RER_{it}^{E}):

$$Misalignment_{it} = RER_{it} - RER_{it}^{E}. \tag{2.1}$$

The equilibrium RER is the real exchange rate that simultaneously attains both domestic equilibrium (i.e. the clearance of the non-tradable sector) and external equilibrium (i.e. the present and future current account balances that are compatible with long-run capital flows) (Nurkse, 1945; Edwards, 1989).[4] These two equilibria are each affected by their own set of domestic and external RER fundamentals, which basically, are domestic and external factors that determine the real exchange rate (see Section 2.3.2).[5]

To construct the RER misalignment index, we use a filter to decompose the RER (both domestic and external) fundamentals into short-run (i.e. cyclical) and long-run (i.e. trend) components.[6] Then, we use the long-run components of the RER fundamentals to construct the equilibrium RER. As such, the difference between the observed RER and the equilibrium RER (i.e. the RER misalignment index) will be driven *only* by the short-run components of (and therefore shocks to) the RER fundamentals.

2.3.1 The Real Effective Exchange Rate

Concerning the real exchange rate, we follow Darvas (2012) and Sekkat (2016) to use the real effective exchange rate, which measures the inflation adjusted value of a country's currency against a basket of currencies of the country's trading partners. To compute this, we need a price index for each country and its trading partners (Chinn, 2006). Due to the availability of data, the most commonly used price index

[4]In other words, the equilibrium real exchange rate is "the value of the real exchange rate that is consistent with the dual objectives of external and internal balance, for specified values of other variables that may influence these objectives. The former refers to a situation in which the value of the current account deficit is one that can be financed by a 'sustainable' level of capital inflows, while the latter refers to a situation in which the market for non-traded goods is in a 'sustainable' equilibrium" (Montiel, 1999, p.219).

[5]Please see MacDonald (2000) for a brief review on the various theoretical and empirical models of equilibrium real exchange rate determination.

[6]For the baseline, we have used the Hodrik-Prescott filter. We have also considered using the Band-Pass filter as a robustness check (see Section 2.6.5).

for this purpose is the consumer price index (CPI). As such, we calculate the real effective exchange rate (which we still call it RER) as

$$RER_{it} = \frac{\prod_{j=1}^{N} E(i,j)_t^{w(j)} \times CPI(i)_t}{\prod_{j=1}^{N} CPI(j)_t^{w(j)}} \tag{2.2}$$

where $E(i,j)$ is the nominal bilateral exchange rate between country i and its trading partner (country j) measured as the country j's currency per unit of country i's currency; CPI is the consumer price index of the home country; $CPI(j)$ is the consumer price index of trading partner country j; and $w(j)$ is the weight that reflects the proportion of a country i's total trade with its partner country j where these weights sum to one over j, i.e. $\sum_{j=1}^{N} w(j) = 1$ (N is the total number of trading partners). According to Eq. (2.2), an increase in the real effective exchange rate index indicates a real exchange rate appreciation of country i's currency, and vice-versa.

2.3.2 The Equilibrium Real Exchange Rate

To estimate the equilibrium RER, we first specify a model that links the real exchange rate to the RER fundamentals. We follow the literature (see, for example, Edwards, 1989; Goldfajn and Valdes, 1999; Elbadawi et al., 2012) to model the real (effective) exchange rate as

$$\begin{aligned} \ln(RER_{it}) = \beta_i + \beta_1 \ln(TOT_{it}) + \beta_2 NFA_{it} + \beta_3 R_t^W + \beta_4 AID_{it} \\ + \beta_5 \ln(PROD_{it}) + \beta_6 \ln(GOV_{it}) + \beta_7 OPEN_{it} + \varepsilon_{it}, \end{aligned} \tag{2.3}$$

where the external fundamentals are the terms of trade (TOT_{it}), net foreign asset (NFA_{it}), international interest rate (R_t^W), and foreign aid as a percentage of GDP (AID_{it}); and the domestic fundamentals are productivity ($PROD_{it}$) (that captures the Balassa-Samuelson effect), the ratio of government expenditure to GDP (GOV_{it}), and trade openness (i.e. the ratio of export and import to GDP) ($OPEN_{it}$).[7]

[7]For a discussion on why these variables are chosen for the real exchange rate model and what their effects (sign-wise) on the real exchange rate are, please see Edwards (1989), Goldfajn and Valdes (1999), and Elbadawi et al. (2012), which we follow here.

A. Estimation

The equilibrium RER is estimated in two steps. In the first step, we estimate the RER model expressed by Eq. (2.3). In the second step, we decompose the RER fundamentals into short and long-run components, and feed the long-run (i.e. trend) components into the estimated model to estimate the equilibrium RER. In doing so, the variation in the misalignment index (see Eq. (2.1)) will be driven solely by short-run shocks to the RER fundamentals. The details are as follows.

Step 1: To estimate Eq. (2.3), we employ three different econometric techniques with error correction formulation that suits non-stationary heterogeneous panels with large N and T: the Mean Group, the Pooled Mean Group and the Dynamic Fixed Effect estimator.[8] The Mean Group estimator is the most general estimator among these three, in that it allows for potential differences in the intercept, the short-run parameters (capturing short-run relationships), the long-run parameters (capturing long-run relationships), and error variances across countries. The Pooled Mean Group estimator is more constrained than the Mean Group estimator in that it restricts the long-run coefficients to be equal across countries, but allows the intercept, short-run coefficients and error variances to potentially differ as before. The Dynamic Fixed Effect estimator is the most restrictive of the three, as it imposes constant short and long-run coefficients across countries, and only allows for potentially heterogeneous intercepts.

Concerning the Pooled Mean Group, Mean Group and Dynamic Fixed Effect estimators, there are trade-offs between consistency and efficiency to consider. If all the long and short-run parameters in the underlying data generating process are heterogeneous, only the (most flexible) Mean Group estimator will be consistent. However, if all the parameters are constant, all three estimators will be consistent but the (most restrictive) Dynamic Fixed Effects estimator will be the most efficient. The Pooled Mean Group estimator lies between the Mean Group and the Dynamic Fixed Effects estimator in terms of the trade-offs between consistency and efficiency,

[8] Appendix B provides a brief discussion on the three estimators.

in that it constrains only a subset of parameters (i.e. the long-run parameters) to be constant, rather than allowing all the parameters to be heterogeneous like the Mean Group estimator or most of the parameters to be fixed like the Dynamic Fixed Effects estimator.

To model the short-run process in real exchange rates, we follow Pesaran et al. (1999) in using the Schwarz Bayesian Information Criterion (SBIC) to determine which RER fundamentals should be modeled with a lag. We find that the terms of trade, productivity, the international interest rate, and net foreign assets should be modeled with one lag, while trade openness, government expenditure, and foreign aid should be modeled without a lag (for this reason, there are no short-run coefficients for trade openness, government expenditure and foreign aid).[9]

Table 2.1 reports our estimates of Eq. (2.3) based on the three approaches. Concerning the long-run parameters, their signs are consistent with what theory predicts (Elbadawi et al., 2012; Ghura and Grennes, 1993; Sekkat, 2016; Schröder, 2013), where on average, (a) an increase in the terms of trade, productivity, government expenditure, international interest rate and net foreign asset result are associated with an RER appreciation, (b) an increase in trade openness and foreign aid inflow are associated with an RER depreciation. Concerning the short-run parameters, productivity is the only variable that has a statistically significant effect on the real exchange rate in all three regression models, where in the short run , an increase in productivity is associated with an RER appreciation on average.

Step 2: To construct the equilibrium RER, we first employ the Hodrick-Prescott (HP) filter to decompose the trend and the cyclical components of the RER fundamentals. The trend component of each fundamental is its permanent component. It is sometimes called the "sustainable fundamental" (Goldfajn and Valdes, 1999; Sekkat and Varoudakis, 2000; Elbadawi et al., 2012), as it is the component in the fundamental that is sustained across time as opposed to the cyclical components that die out more rapidly.

[9]The estimated parameters of the Mean Group and the Pooled Mean Group estimators are robust to the choice of the lag length order if T is sufficiently large (Pesaran et al., 1999).

Table 2.1: The Long-run and Short-run Estimates of the Real Exchange Rate Model

	(1)	(2)	(3)
	Estimation techniques		
	Mean Group (MG)	Pooled Mean Group (PMG)	Dynamic Fixed Effects (DFE)
Long-run coefficients:			
Terms of trade (in logs)	0.516*	0.330***	-0.011
	(0.290)	(0.076)	(0.100)
Productivity (in logs)	0.237	0.235***	0.337***
	(0.199)	(0.045)	(0.066)
Government expenditure (in logs)	0.145	0.511***	0.247***
	(0.132)	(0.060)	(0.070)
Foreign aid	-0.004	-0.008***	-0.003
	(0.008)	(0.002)	(0.003)
Trade openness	-0.004*	-0.004***	-0.003***
	(0.002)	(0.001)	(0.001)
International interest rate	-0.003	0.032***	0.042***
	(0.011)	(0.006)	(0.009)
Net foreign asset	0.083	0.148***	0.095**
	(0.158)	(0.048)	(0.046)
Short-run coefficients:			
Error correction coefficient	-0.546***	-0.187***	-0.225***
	(0.049)	(0.034)	(0.019)
D.(terms of trade, logs)	-0.071	-0.066	-0.049
	(0.053)	(0.040)	(0.034)
D.(productivity, logs)	0.122**	0.311***	0.318***
	(0.060)	(0.059)	(0.033)
D.(international interest rate)	0.001	-0.001	-0.004
	(0.004)	(0.002)	(0.003)
D.(net foreign asset)	0.099**	0.049	-0.017
	(0.041)	(0.032)	(0.019)
Constant	2.822***	0.568***	1.221***
	(0.481)	(0.096)	(0.186)
N	1050	1050	1050

Note: The dynamic specification of the real exchange rate model presented here is chosen using the Schwarz Bayesian information criterion (SBIC), following Pesaran et al. (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To estimate the equilibrium RER, we feed the long-run sustainable components of the RER fundamentals, collectively represented by the vector $\mathbf{F}_{it}^{S}$, into the estimated version of the RER model expressed by Eq. (2.3):[10]

$$RER_{it}^{E} = \tilde{\gamma}_i + \widehat{\boldsymbol{\beta}}'\mathbf{F}_{it}^{S}. \tag{2.4}$$

The vector $\mathbf{F}_{it}^{S}$ contains the sustainable components of the RER fundamentals and $\widehat{\boldsymbol{\beta}}$ is the factor loading. The parameter $\tilde{\gamma}_i$ is a scaled country specific intercept term, which is given by

$$\tilde{\gamma}_i = \overline{RER}_i - \widehat{\boldsymbol{\beta}}'\overline{\mathbf{F}}_i^{S} \tag{2.5}$$

where $\overline{RER}_i$ is the average observed RER and $\overline{\mathbf{F}}_i$ is the vector of the average sustainable RER fundamentals. The scaled intercept term, expressed by Eq. (2.5), ensures that for each country, the RER misalignment index has an expected value of zero. This zero expectation ensures that the actual real exchange rate will always revert to its long-run equilibrium should they diverge, so that any deviation in the actual real exchange rate from equilibrium represents a temporary than a permanent misalignment.[11]

To proceed further, by substituting $\tilde{\gamma}_i$ from Eq. (2.5) into Eq. (2.4), we obtain a second expression for the equilibrium RER as

$$RER_{it}^{E} = \overline{RER}_i + \widehat{\boldsymbol{\beta}}'(\mathbf{F}_{it}^{S} - \overline{\mathbf{F}}_i^{S}). \tag{2.6}$$

This expression shows that for each country i, the equilibrium RER is equal to the sum of the average RER and the weighted deviation of RER fundamentals from their averages.

Further Remarks: For the baseline, we use the Pooled Mean Group estimates of Eq. (2.3) to construct the equilibrium RER expressed by Eq. (2.6). This is because the Pooled Mean Group estimator lies in between the Mean Group and the Dynamic

[10]Eq. (2.3) is estimated either by the Mean Group, Pooled Mean Group, or the Dynamic Fixed Effects estimator.

[11]See Appendix C in Elbadawi et al. (2012) for more detail.

Fixed Effects estimators in terms of the trade off between consistency and inefficiency. Importantly, we find that our results (i.e. the effects of RER misalignment on conflict) are not sensitive to the choice of using the Mean Group or Dynamic Fixed Effects estimator when estimating the equilibrium RER.

2.3.3 The Misalignment Index

Once the equilibrium RER is computed in Step 2, we may take the difference between the observed RER in Eq. (2.2) and the estimated equilibrium RER in Eq. (2.6) to construct the RER misalignment index

$$Misalignment_{it} = \underbrace{(RER_{it} - \overline{RER}_i)}_{(I)} - \widehat{\boldsymbol{\beta}}' \underbrace{(\mathbf{F}^S_{it} - \overline{\mathbf{F}}^S_i)}_{(II)}. \tag{2.7}$$

Eq. (2.7) contains two parts. Part (I) is the difference between the actual RER and its average value. Part (II) reflects the adjustment of the real exchange rate that should occur in equilibrium. If the difference between the actual RER and its average value exceeds the appreciation (or depreciation) that should occur in equilibrium, the real exchange rate is overvalued. This is represented by $Misalignment_{it} > 0$. If the difference between actual RER and its average value falls short of the equilibrium appreciation (or depreciation), the real exchange rate is undervalued. This is represented by $Misalignment_{it} < 0$.

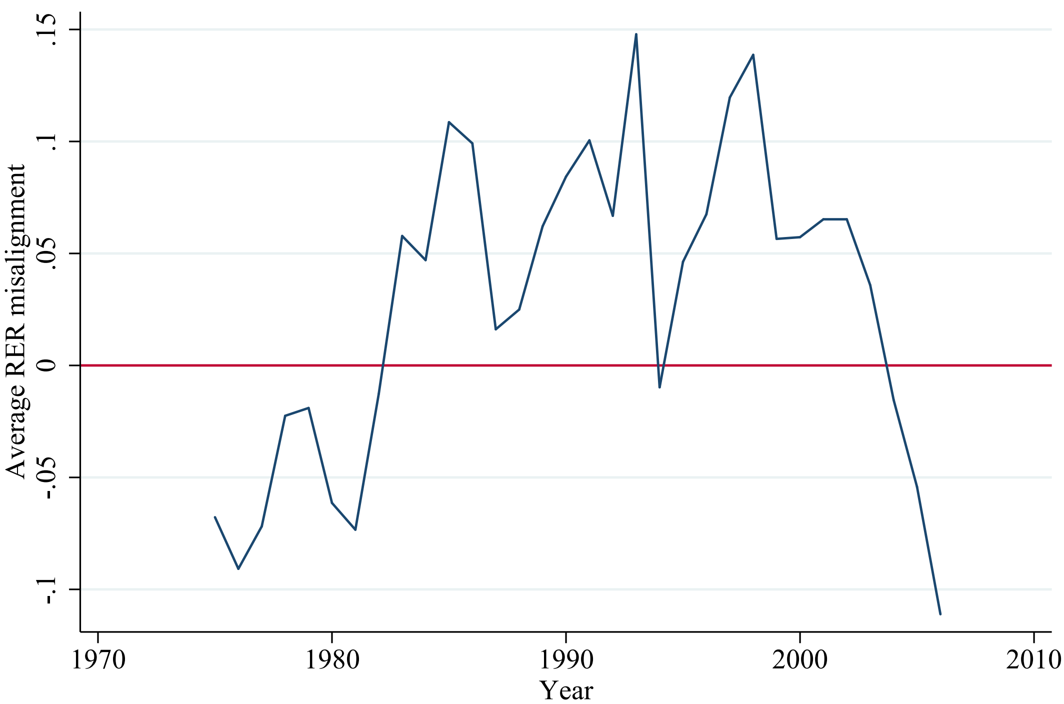
Further manipulation of Eq. (2.7) reveals where the variation in $Misalignment_{it}$ comes from. Let $\mathbf{F}^T_{it}$ represent the vector of short-run transitory components of the RER fundamentals and $\overline{\mathbf{F}}^T_i$ their averages. We may decompose the RER fundamentals into $\mathbf{F}_{it} = \mathbf{F}^T_{it} + \mathbf{F}^S_{it}$, and their averages into $\overline{\mathbf{F}}_i = \overline{\mathbf{F}}^T_i + \overline{\mathbf{F}}^S_i$. If we substitute the estimated $RER_{it} = \widehat{\gamma}_i + \widehat{\boldsymbol{\beta}}'\mathbf{F}_{it} + \widehat{\varepsilon}_{it}$ and its average $\overline{RER}_i = \widehat{\gamma}_i + \widehat{\boldsymbol{\beta}}'\overline{\mathbf{F}}_i + \overline{\widehat{\varepsilon}_i}$ into Eq. (2.7), we obtain another expression for RER misalignment as

$$\begin{aligned} Misalignment_{it} =& \widehat{\boldsymbol{\beta}}'[(\mathbf{F}_{it} - \mathbf{F}^S_{it}) - (\overline{\mathbf{F}}_i - \overline{\mathbf{F}}^S_i)] + (\widehat{\varepsilon}_{it} - \overline{\widehat{\varepsilon}}_i) \\ =& \widehat{\boldsymbol{\beta}}'[\mathbf{F}^T_{it} - \overline{\mathbf{F}}^T_i] + (\widehat{\varepsilon}_{it} - \overline{\widehat{\varepsilon}}_i). \end{aligned} \tag{2.8}$$

Eq. (2.8) suggests that the variation in the RER misalignment index comes from the weighted deviations of the RER short-run components from their averages and short-run idiosyncratic RER shocks, represented by $(\widehat{\varepsilon}_{it} - \overline{\widehat{\varepsilon}}_i)$. Thus, our RER misalignment index is driven only by the short-run transitory components of the RER fundamentals as well as idiosyncratic shocks to the real exchange rate.

In Figure 2.1, we plot the average real exchange rate misalignment index for the whole sub-Saharan African region in the given sample period. With the exception of the large undervaluation that has occurred in recent years, the average real exchange rate in the SSAs has been significantly overvalued at various times during the sample period. In Appendix C, we plot the RER misalignment index for each country. We find that the real exchange rate tends to be overvalued for larger countries such as Angola, Chad, Central Africa republic, Congo Democratic Republic, Cote D'IVoire, Equatorial Guinea, Uganda and Zambia, which incidentally are countries where civil conflict is more common.

Figure 2.1: Average RER misalignment in sub-Saharan Africa



Note: This figure plots the average RER misalignment index for sub-Saharan Africa for each year by averaging the RER misalignment indices of the 35 SSAs in our sample.

2.4 Data

Our panel data consists of 35 SSAs from 1975-2006, listed in Table A1 of Appendix A. The variables used in this paper, their definitions and data sources are given in Table A2 of Appendix A.

Our data on civil conflict comes from the joint armed conflicts dataset of the Uppsala Conflict Data Program (UCDP) and the International Peace Research Institute's (PRIO) Centre for the study of civil war. The UCDP/PRIO (v.4-2015) codebook defines civil conflict as conflict involving government or territory or both where the use of armed force between two parties results in 25 or more battle-related deaths. We focus exclusively on internal armed civil conflict, which is "conflict (that) occurs between the government of a state and one or more internal opposition group(s) without intervention from other states" (Pettersson and Wallensteen, 2015, p.9).

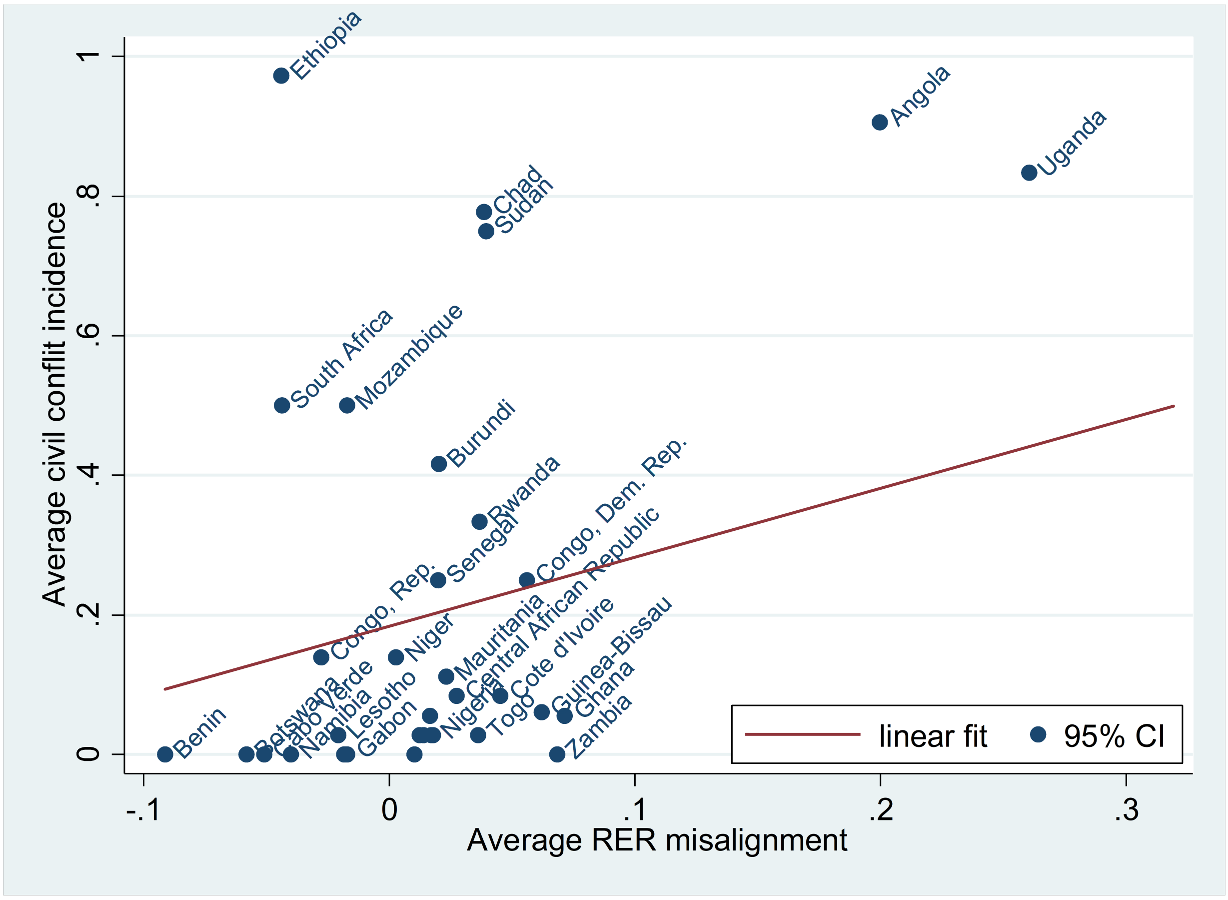
Our main dependent variable is the incidence of civil conflict. This is represented by a dummy variable that indicates if a country for a given year is involved in a new or ongoing war that has resulted in at least 25 battle related deaths per year. To save space, we have considered but do not report the results related to the onset of civil conflict, or for small versus large scale conflict.[12]

Table A3 in Appendix A provides the descriptive statistics on civil conflict incidence. Over the sample period, civil conflict occurs in 21.30% of the country-year observations, which suggests that the occurrence of civil conflict is rather common and widespread in the SSAs. To see the link between civil conflict incidence and RER misalignment in sub-Saharan Africa, we plot the the average conflict incidence against the average RER misalignment index, over the sample period, for each SSA in Figure 2.2. Here, we find that there is a positive cross-sectional association between average conflict incidence and average RER misalignment. The strong positive correlation between the two implies that countries with large RER overvaluation have also higher incidence of civil conflict. Angola and Uganda, in particular, have larger RER

[12]Civil conflict onset is represented by a dummy variable that indicates the year in which there is a new civil conflict outbreak (Miguel et al., 2004) (the years in which there is an ongoing war are coded as zero). Small scale conflict conflict is coded as 1 if country-year observations have 25-1000 deaths per year. Large scale conflict is coded as 1 if country-year observations have more than 1000 deaths per year.

overvaluations and higher civil conflict incidences on average. Ethiopia, by contrast, has a large average civil conflict incidence but a small average RER misalignment. For countries such as Ethiopia, it is possible that the incidence of civil conflict is influenced by other factors, such as rainfall shocks, as a large proportion of the labor force (more than 85% for Ethiopia) works in agriculture.

Figure 2.2: Average civil conflict incidence and average RER misalignment for SSAs



Note: This figure shows the scatter plot of average civil conflict incidence and average RER misalignment index for countries in sub-Saharan Africa.

2.5 The Model

Our main estimating equation relates the incidence of civil conflict ($conflict_{it}$) to the RER misalignment index ($Misalignment_{it}$) plus a vector of control variables ($\mathbf{X}_{it}$):

$$Conflict_{it} = \gamma + \beta Misalignment_{it} + \boldsymbol{\delta}'\mathbf{X}_{it} + \mu_i + \mu_t + \varepsilon_{it} \tag{2.9}$$

where μ_i is the country fixed effect, μ_t is the year fixed effect, and ε_{it} is the error term. We estimate Eq. (2.9) using OLS regression. For inference, we use robust standard errors clustered at the country level.

2.6 Results

2.6.1 Baseline Results

We first estimate Eq. (2.9) without covariates and report these results in Table 2.2 as our baseline. In Column (1), we estimate the model without fixed effects. In Column (2), we include country fixed effects only. In Column (3), we include both country and year fixed effects. In all three cases, we find that RER misalignment has a positive and statistically significant effect (at the 5% level) on conflict incidence.

These results suggest two things. Firstly, the effect of RER misalignment on conflict does not appear to be driven by unobserved country heterogeneity and common trends. Secondly, the positive coefficient on the RER misalignment index suggests an RER overvaluation is associated with a higher risk of conflict.

For example, based on Column (3), a one-standard deviation increase in the misalignment index (i.e. one-standard deviation RER overvaluation) is associated with a 4 percentage points increase in the probability of conflict on average. This effect size appears to be nontrivial. For example, for Togo, a country with an RER misalignment index around the SSAs' average, the model predicts that the probability of civil conflict would *double* from 4% to 8% if its RER misalignment index increases by one standard deviation. Therefore, from a policy perspective, governments may help to reduce the risk of civil conflict by reducing the misalignment of their real exchange rates.

2.6.2 With Covariates

Controlling for macroeconomic factors Several macroeconomic factors may affect the likelihood of civil conflict. In literature, it has been suggested that civil conflict could be influenced by GDP per capita (Collier, 2008; Blattman and Miguel,

Table 2.2: The Effect of RER Misalignment on Civil Conflict: Baseline Results

	(1)	(2)	(3)
Dependent variable:	Incidence of civil conflict		
Misalignment	0.137**	0.135**	0.121**
	(0.057)	(0.056)	(0.057)
Country FE	No	Yes	Yes
Year FE	No	No	Yes
Constant	0.212***	0.206***	0.207***
	(0.049)	(0.002)	(0.053)
N	1076	1076	1076
R^2	0.0212	0.023	0.050

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2010), trade openness (i.e. total trade flows over GDP) (Magee and Massoud, 2011; Janus and Riera-Crichton, 2015), government expenditure (Fearon and Laitin, 2003), total population (Raleigh and Hegre, 2009), foreign aid (De Ree and Nillesen, 2009; Nunn and Qian, 2014), institutions (Fearon and Laitin, 2003; Miguel et al., 2004; Goldstone et al., 2010; Bates, 2008) and domestic policy (Hull and Imai, 2013). Here, we show that RER misalignment is statistically significant for conflict despite controlling for these macroeconomic factors.

Our data on GDP per capita, trade openness, government expenditure (as a percentage of GDP), total population and foreign aid (as percentage of GDP) are taken from the World Development Indicators. Concerning data on institutions, we use the Polity2 score measure from the polity IV project data base (Marshall and Jaggers, 2009). The Polity2 score variable ranges from -10 to +10. Positive values of Polity2 indicate democracies while negative values represent autocracies. A Polity2 score of zero indicates a political institution that is neither democratic nor autocratic. For our regression, we follow Fearon and Laitin (2003) and Janus and Riera-Crichton (2015) to construct an intermediate democracy dummy variable that is equal to one when Polity2 scores falls in [-5, 5] range and zero otherwise. Countries with Polity2 scores within [-5, 5] are those, according to Bates (2008), that have "partial" or "unconsolidated" democracies, where conflict incidence tends to be disproportionately larger as well (see e.g. Bates, 2008). Finally, shifts in domestic macroeconomic policies may also affect the likelihood of civil conflict. Following the civil conflict literature (Hull and Imai, 2013), we control for the inflation rate of each country, which is available from the World Development Indicators, to capture domestic macroeconomic policy changes.

In Table 2.3, we report the coefficient on the RER misalignment index only. In the row "$t-1$", we report the coefficient on the RER misalignment index controlling for the *first* lag of the macroeconomic factor(s) indicated in the column header (e.g. GDP per capita in Column (1), Openness in Column (2), and all covariates mentioned in the above in Column (8)). Similarly, in the row "$t-2$", we report the coefficient on the RER misalignment index controlling for the *second* lag of the covariate(s), and so on.

Whether we control for the first, second, third, forth or fifth lags of one or all the covariates, we find that the effect of RER misalignment index on civil conflict incidence is always positive and statistically significant at least at the 10% level. Moreover, the coefficients on the RER misalignment index range from 0.110 (Column (2)) to 0.150 (Column (8)), which are close to the two-way fixed effect estimate from the baseline regression (see Column (3) of Table 2.2). Therefore, RER misalignment has an effect on conflict beyond the effects of these macroeconomic factors at various lag lengths.

Table 2.3: The Coefficient of RER Misalignment Controlling for Additional Macroeconomic Covariates at Different Lags

	1	2	3	4	5	6	7	8
Covariates:	GDP per capita	Openness	Gov. expend.	Population	Aid	Int. democracy	Inflation	All covariates
Lag length:	*Dependent Variable*: Civil conflict incidence							
$t-1$	0.130**	0.110**	0.136**	0.118**	0.118**	0.113*	0.132**	0.132**
	(0.057)	(0.050)	(0.062)	(0.056)	(0.057)	(0.057)	(0.057)	(0.052)
$t-2$	0.138**	0.110**	0.128**	0.118**	0.116**	0.112*	0.138**	0.128**
	(0.059)	(0.050)	(0.057)	(0.056)	(0.057)	(0.057)	(0.058)	(0.052)
$t-3$	0.149**	0.113**	0.123**	0.118**	0.117**	0.111*	0.145**	0.137**
	(0.062)	(0.051)	(0.056)	(0.056)	(0.056)	(0.056)	(0.060)	(0.057)
$t-4$	0.158**	0.117**	0.122**	0.118**	0.123**	0.112*	0.145**	0.150**
	(0.065)	(0.051)	(0.056)	(0.056)	(0.055)	(0.055)	(0.060)	(0.058)
$t-5$	0.138**	0.118**	0.119**	0.118**	0.125**	0.115**	0.131**	0.122**
	(0.061)	(0.050)	(0.056)	(0.056)	(0.054)	(0.055)	(0.056)	(0.053)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Controlling for rainfall and commodity price shocks It has been found that the risk of civil conflict in the SSAs may increase with negative climate shocks (Miguel et al., 2004; Burke et al., 2009; Hsiang et al., 2013) and negative shocks to the price of commodities that the SSAs export (Brückner and Ciccone, 2010; Hull and Imai, 2013; Bazzi and Blattman, 2014). Here, we examine whether RER misalignment has explanatory power on conflict once we control for rainfall and commodity price shocks.

Concerning rainfall shocks, we use the growth in rainfall based on rainfall data from the NASA Global Precipitation Climatology Project (GPCP), following Miguel et al. (2004), and Brückner and Ciccone (2010).[13] Concerning commodity price shocks, we construct a growth series based on the Brückner and Ciccone (2010) index of export commodity prices defined as $Commodity\_price_{it} = \sum_{c=1}^{19} \kappa_{ci} P_{ct}$ for country i in year t, where κ is the fixed export share of commodity c in country i, and P_{ct} is the period t price series of commodity c. The commodity price data used by Brückner and Ciccone (2010) is obtained from the International Monetary Fund (2009), and their fixed export shares on 19 primary commodities are obtained from Deaton (1990).

Table 2.4 reports the regression results when we control for rainfall shocks (at time t, $t-1$ and $t-2$) (Column (1)), commodity price shocks (at time t, $t-1$ and $t-2$) (Column (2)), and both rainfall and commodity price shocks (Column (3)). Despite doing so, we find that RER misalignment is statistically significant with a similar effect size as the baseline estimate. This suggests that RER misalignment has explanatory power on conflict beyond what may be explained by arguably two of the most important factors in the literature: rainfall and commodity price shocks.

2.6.3 Overvaluation, Undervaluation and Civil Conflict

Up to now, our analysis assumes that RER overvaluation (i.e. $Misalignment_{it} > 0$) and RER undervaluation (i.e. $Misalignment_{it} < 0$) affect civil conflict

[13]We use version 2.0 of the GPCP rainfall data set, which is based on rainfall data collected from satellites and rain gauges.

Table 2.4: The Effect of RER Misalignment, Rainfall and Commodity Price Shocks on Civil Conflict

	(1)	(2)	(3)
Dependent variable:	Incidence of civil conflict		
Misalignment	0.170**	0.177**	0.174**
	(0.083)	(0.083)	(0.083)
Rainfall shock, t	0.029		0.030
	(0.064)		(0.063)
Rainfall shock, $t-1$	-0.083		-0.082
	(0.071)		(0.070)
Rainfall shock, $t-2$	-0.104*		-0.106*
	(0.057)		(0.058)
Commodity price shock, t		0.086	0.085
		(0.075)	(0.074)
Commodity price shock, $t-1$		-0.011	-0.015
		(0.090)	(0.092)
Commodity price shock, $t-2$		0.080	0.083
		(0.063)	(0.063)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	0.259***	0.240***	0.235***
	(0.052)	(0.063)	(0.063)
N	725	725	725
R^2	0.058	0.058	0.063

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

symmetrically.[14] However, RER overvaluation and undervaluation are different types of RER distortions with possibly different effects on growth (Nouira and Sekkat, 2012; Schröder, 2013).[15]

To investigate if the effect of RER misalignment is asymmetric, we split the RER misalignment index into two parts – an RER overvaluation index defined as the positive part of $Misalignment_{it}$, and an RER undervaluation index defined as the negative part of $Misalignment_{it}$. We then repeat the baseline regressions by including both of them as separate regressors, instead of a single RER misalignment index.

Table 2.5 shows that RER overvaluation has a positive and statistically significant effect on conflict. However, RER undervaluation is statistically insignificant. The coefficients on the RER overvaluation index, which range from 0.202 (Column (3)) to 0.210 (Column (2)), are also much larger than the coefficients on the baseline RER misalignment index (see Table 2.2). Together with the fact that RER undervaluation is statistically insignificant, this suggests that the effect RER misalignment as a whole is driven mainly by the effect of RER overvaluation.

2.6.4 System GMM and IV Regression

RER misalignment is driven by shocks to the RER fundamentals. Here, we employ two approaches to check if the effect of RER misalignment on conflict is merely capturing the reverse causal effect.

Our first approach is to estimate a dynamic panel model using system Generalized Method of Moments (system GMM) (Blundell and Bond, 1998). The idea of using a dynamic panel model comes from the idea that if current conflict affects RER misalignment in the next period, then one reduced-form approach of addressing this reverse causal effect (from conflict to RER misalignment) is to include the lag of

[14]A bulk of the literature that studies the effect of RER misalignment on growth assumes that the effect of RER undervaluation and RER overvaluation on growth is equal and opposite (see Ghura and Grennes (1993), Elbadawi et al. (2012), Rodrik (2008), Goldfajn and Valdes (1999) for example).

[15]For example, Nouira and Sekkat (2012) show that an increase in RER overvaluation has a negative and statistically significant effect on growth, but find no statistically significant relationship between undervaluation and growth. Schröder (2013) finds that an increase in RER overvaluation has large negative effects on growth, but an increase in RER undervaluation reduces growth if and only if the undervaluation persists for sufficiently longer time periods.

Table 2.5: The Effect of RER Overvaluation and Undervaluation on Civil Conflict

	(1)	(2)	(3)
Dependent variable:	Civil conflict incidence		
Overvaluation	0.205**	0.210**	0.202**
	(0.081)	(0.080)	(0.082)
Undervaluation	0.038	0.029	0.006
	(0.082)	(0.084)	(0.079)
Country FE	No	Yes	Yes
Year FE	No	No	Yes
Constant	0.198***	0.199***	0.188***
	(0.053)	(0.013)	(0.057)
N	1105	1105	1105
R^2	0.023	0.026	0.052

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

conflict as a control variable. As such, we employ system GMM to estimate the following model

$$Conflict_{it} = \gamma + \delta Conflict_{it-1} + \beta Misalignment_{it} + \boldsymbol{\delta}'\mathbf{X}_{it} + \mu_i + \mu_t + \varepsilon_{it}. \quad (2.10)$$

Our second approach is to employ an external instrument for RER misalignment. To do so, we follow Habib et al. (2017) to construct a Bartik-style instrument (Bartik, 1991) by interacting (i) global capital flows and (ii) the country's degree of *de jure* financial openness. The idea is that capital flows are significantly influenced by global factors (Forbes and Warnock, 2012) and an increase in capital inflow to a country is typically followed by an appreciation in the country's real exchange rate (Habib et al., 2017). Habib et al. (2017) posit that capital flows, which are driven by global push factors, generate exogenous variations in the real exchange rate. As such, their instrument should in principle affect RER misalignment, given that it is a function of the real exchange rate.

As a comment, like economic growth studied by Habib et al. (2017), conflict could be directly affected by global factors (which drive capital flows). To eliminate the confounding effects of such global factors, we use year fixed effects. Note that year fixed effects will not partial out Habib et al.'s (2017) as it is both cross-sectionally and time-varying. As such, following a similar argument as Habib et al. (2017), once country and year fixed effects are controlled for, it is reasonable to expect that the Habib et al. (2017) instrument will not directly affect conflict except only through its effect on RER misalignment.

Tables (2.6) and (2.7) present the system GMM and IV estimates, respectively. In Table (2.6), the system GMM estimates show that RER misalignment has a statistically significant effect on conflict (at the 1% level) despite controlling for the lag of conflict, rainfall shocks and/or commodity price shocks. The system GMM estimates of the effect size of RER misalignment are also larger than our baseline estimates. This provides some comfort, in the sense that the baseline estimates are possibly more conservative than what the true effect of RER misalignment may be.

In Table (2.7), the first stage results reported in Panel (B) show that Habib et al.'s (2017) has a Kleibergen-Paap F-statistic that exceeds the rule-of-thumb threshold of 10, suggesting that it is an adequately strong instrument for RER misalignment. The coefficient on Habib et al.'s (2017) instrument is also positive for RER misalignment. This suggests that world capital inflows have, on average, a stronger influence in misaligning a country's real exchange rate the more financially open the country is.

The second stage results reported in Panel (A) affirm once more that RER misalignment has a positive and statistically significant effect on conflict even after controlling for rainfall and/or commodity price shocks. Interestingly, the IV estimates produce a much larger effect size of RER misalignment than the non-IV estimates do. For example, the effect of RER misalignment is more than three times larger for the IV estimates (see Table 2.7) than for the baseline estimates (see Table 2.4). This suggests that our baseline estimates are conservative about the actual effect size of RER misalignment on conflict. Importantly, even based on these conservative estimates, we find that the impact of RER misalignment is nontrivial.

Table 2.6: RER Misalignment and Civil Conflict: System GMM Estimates

	(1)	(2)	(3)
Dependent variable:		Civil conflict incidence	
Civil conflict incidence, $t-1$	-0.499***	-0.501***	-0.500***
	(0.036)	(0.035)	(0.035)
RER misalignment	0.281***	0.280***	0.280***
	(0.061)	(0.061)	(0.061)
Rainfall shock, t	0.078		0.072
	(0.149)		(0.147)
Rainfall shock, $t-1$	-0.029		-0.033
	(0.097)		(0.097)
Rainfall shock, $t-2$	0.010		0.001
	(0.136)		(0.136)
Commodity price shock, t		0.139	0.139
		(0.143)	(0.142)
Commodity price shock, $t-1$		0.092	0.092
		(0.123)	(0.123)
Commodity price shock, $t-2$		-0.058	-0.054
		(0.104)	(0.103)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
AR(2)	0.899	0.859	0.818
Hansen test (p-value)	1.000	1.000	1.000
N	519	519	519

Note: Robust standard errors are reported in the parentheses. *, **, *** represent the level of statistical significance at 1%, 5%, and 10%, respectively. The year fixed effects, the commodity price shocks and the rainfall shocks are treated as strictly exogenous. The first year lag of civil conflict incidence and the RER misalignment index are treated as endogenous. Moreover, the Hansen test for over-identifying restrictions and the second order test for autocorrelation suggest that the validity of the SGMM moment conditions are not rejected.

Table 2.7: RER Misalignment and Civil Conflict: An External Instrument Approach

	(1)	(2)	(3)
	Panel A: Second-stage estimates		
Dependent Variable:	Civil conflict incidence		
RER misalignment	0.703**	0.636**	0.599**
	(0.337)	(0.299)	(0.299)
Rainfall shock, t	0.004		0.004
	(0.074)		(0.072)
Rainfall shock, $t-1$	-0.093		-0.096
	(0.086)		(0.084)
Rainfall shock, $t-2$	-0.114		-0.127*
	0.069		(0.067)
Commodity price shock, t		0.098	0.096
		(0.074)	(0.074)
Commodity price shock, $t-1$		0.030	0.025
		(0.081)	(0.081)
Commodity price shock, $t-2$		0.135*	0.138*
		(0.078)	(0.077)
	Panel B: First-stage estimates		
Dependent Variable:	RER misalignment		
World capital flows × financial openness, $t-1$	0.011***	0.013***	0.012***
	(0.003)	(0.003)	(0.004)
	Coefficients on rainfall and commodity price shocks are suppressed		
Kleibergen-Paap F-statistic	11.627	12.860	12.726
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of countries	30	30	30
Observations	634	634	634
Pseudo R^2	0.160	0.172	0.173

Note: ***Panel A*** presents the second stage estimates of the 2SLS estimation. ***Panel B*** reports the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors reported in parenthesis. Other controls include the first year lags of trade openness, inflation, per capita GDP, net capital inflows, and de jure financial openness. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6.5 Further Robustness Checks

In this section, we provide additional robustness checks that detail the motivation of each tests, and what we have observed from them. In each of these exercises, we find robustly that RER misalignment is positively associated with the probability of civil conflict.

Alternative estimation methods In section 2.6.1, we estimate Eq. (2.9) by OLS regression (i.e. simple linear regression and fixed effects regression). Here, we consider three alternative methods of estimating Eq. (2.9): the Probit, Random Effects Logit, and the Fixed Effects Logit approach. All these estimation techniques have been implemented before in this literature (Bazzi and Blattman, 2014).

For the Probit, Random Effects Logit, and Fixed Effects Logit approach, Columns (1)-(3) of Table 2.8 present the estimates of the average marginal effect of RER misalignment on the incidence of civil conflict. Based on these estimation methods, we find that RER misalignment has a positive effect that is statistically significant at the 1% level. Thus, we may conclude that the positive effect of RER misalignment on civil conflict observed in the baseline regression is robust to the estimation methods chosen.

Table 2.8: The Effect of RER Misalignment on Civil Conflict: Using Alternative Estimation Methods

	(1)	(2)	(3)
Estimation Technique:	Probit	Random Effects Logit	Fixed Effects Logit
Dependent variable:	Incidence of civil conflict		
Misalignment	1.096***	2.120***	2.134***
	(0.333)	(0.612)	(0.766)
Country FE	No	No	Yes
Year FE	No	Yes	Yes
Constant	1.455***	-2.785***	–
	(0.260)	(0.802)	–
N	1076	1076	779

Note: Robust standard errors clustered at the country level are reported in the parentheses for the probit and random Effects logit estimators. And bootstrap standard errors are reported for fixed effects logit estimator. We report the average mariginal effects for the probit and the random effects logit estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Alternative RER misalignment index In Section A., we show that the equilibrium RER, which is a required component in computing the RER misalignment index, is constructed by using the parameters of the RER model (i.e. Eq. (2.3)). In that section, we estimate these parameters by the Mean Group, Pooled Mean Group, or Dynamic Fixed Effects estimator. For our baseline regression, we employ the Pooled Mean Group estimator to estimate the parameters of the RER model, which are then used in computing the equilibrium RER (and thus the RER misalignment index).

Instead of the Pooled Mean Group estimator, we employ the Mean Group or the Dynamic Fixed Effects estimator to compute the equilibrium RER, and thus, the RER misalignment index (see Appendix B for a more detailed comparison of the Mean Group, Pooled Mean Group and the Dynamic Fixed Effects estimator). As Table 2.9 demonstrates, using the RER misalignment index constructed from the Mean Group or the Dynamic Fixed Effects estimator does not affect the sign and statistical significance of the association between RER misalignment and conflict. In fact, the alternative RER misalignment indices have the similar effect size and statistical significance to the baseline RER misalignment index (see Table 2.2). Therefore, the effect of RER misalignment on civil conflict is not affected by the econometric method used when constructing the equilibrium RER, and thus, the RER misalignment index.

Band-Pass filter Recall, that to construct the RER misalignment index in Step 2 of Section (A.), we have used the Hodrick-Prescott (HP) filter to decompose the long-run (permanent) and the short-run (cyclical) components of the external fundamentals.

In Table 2.10, we show that our results are robust to using the Band-Pass (BP) filter. As Table 2.10 shows, the coefficient on the BP filter-based RER misalignment index is statistically significant, with a value ranging from 0.123 in Column (3) when both country and year fixed effects are included, to 0.133 when none of the fixed effects are included. These values are close to the 0.121 to 0.137 range reported in Table 2.2 for the coefficient on the baseline (HP filter-based) RER misalignment index.

Table 2.9: The Effect of RER Misalignment on Civil Conflict: Using Alternative Misalignment Indices

	(1)	(2)	(3)	(4)
Equilibrium RER is estimated by:	Mean Group estimator		Dynamic Fixed Effect estimator	
Dependent variable:	Civil conflict incidence			
Misalignment-MG	0.091	0.127**		
	(0.057)	(0.062)		
Misalignment-DF			0.089	0.126**
			(0.057)	(0.062)
Country FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Constant	0.211***	0.104	0.210***	0.098
	(0.001)	(0.063)	(0.002)	(0.063)
N	1062	1062	1062	1062
R^2	0.009	0.049	0.009	0.049

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

Table 2.10: The Effect of RER Misalignment on Civil Conflict: Using Band Pass Filter

	(1)	(2)	(3)
Dependent variable:	Incidence of civil conflict		
Misalignment	0.132**	0.133**	0.123**
	(0.055)	(0.055)	(0.055)
Country FE	No	Yes	Yes
Year FE	No	No	Yes
Constant	0.223***	0.222***	0.205***
	(0.052)	(0.000)	(0.054)
N	973	973	973
R^2	0.017	0.017	0.045

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

Sub-sample analysis and the Washington Consensus In 1990, the International Monetary Fund (IMF), World Bank, and the US Treasury Department came together to promote a set of policy prescriptions, collectively known as the Washington Consensus, to help developing countries facing problems with macroeconomic instability such as distortions to the real exchange rate (Williamson, 1990). Following these recommendations, many developing countries adopted reforms packages and loans from institutions such as the World Bank and the IMF. Because the real exchange rates of these recipient countries could be unstable prior to the 1990, but more stable after the reforms, it would be useful to check if our results are driven by the association between RER misalignment and conflict only for a sub-period within our sample.

To do so, we divide the sample into two shorter regimes before and after the Washington Consensus and repeat our baseline regressions based on each of these subsamples. Columns (1)-(2) of Table 2.11 report our estimates for the 1975-1990 period, and Columns (3)-(4) for the 1991-2006 period. For both sub-samples, we find that RER misalignment has a positive and statistically effect (at the 1% level) on civil conflict. Furthermore, the effect of RER misalignment on conflict appears to be stronger during the post-Washington Consensus period. Therefore, the adverse effect of RER misalignment on civil conflict can be observed for the whole sample period, and does not appear to be mitigated by the Washington Consensus.

Table 2.11: The Effect of RER Misalignment on Civil Conflict: Sub-sample Analysis

	(1)	(2)	(3)	(4)
	1975-1990		1991-2006	
Dependent variable:	Incidence of civil conflict			
Misalignment	0.106***	0.104***	0.182***	0.160***
	(0.030)	(0.031)	(0.048)	(0.050)
Country FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Constant	0.173***	0.226***	0.234***	0.218***
	(0.010)	(0.038)	(0.011)	(0.045)
N	516	516	560	560
R^2	0.026	0.046	0.027	0.057

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

Controlling for the lags of RER misalignment In this exercise, we add the one and two year lags of the RER misalignment index to the baseline regressions.[16] In these new regressions, Table 2.12 shows that only the coefficients on the contemporaneous RER misalignment index are statistically significant; the coefficients on the lagged RER misalignment are statistically insignificant. In the case where both country and fixed effects are controlled for (Column (3)), the coefficient on the contemporaneous RER misalignment index is 0.180, which is close to the baseline estimate of 0.121 (Column (3) of Table 2.2).

[16]Note that such type regression specification (i.e. adding one or more lags) is strongly criticized by recent civil conflict studies (see Ciccone (2013) and Chassang and Padro-i Miquel (2009), for example) when the shock that affects civil conflict is a transitory shock. Transitory shocks (e.g. rainfall growth shock) are mean reverting (stationary). The mean-reverting property of the shock leads the coefficient of the contemporaneous value of the shock and the coefficient of its lag to have opposite signs. For instance, when the first year lag of rainfall growth shock increases the likelihood of civil conflict, then the contemporaneous rainfall growth shock should reduce civil conflict which makes difficult to identify the effect the shock on civil conflict. The same critique applies to the RER misalignment index as it is mean reverting as well.

Table 2.12: The Effect of RER Misalignment and Its Lags on Civil Conflict

	(1)	(2)	(3)
Dependent variable:		Civil conflict incidence	
RER misalignment, t	0.174**	0.184**	0.180**
	(0.081)	(0.084)	(0.082)
RER misalignment, $t-1$	-0.012	-0.010	-0.009
	(0.052)	(0.051)	(0.052)
RER misalignment, $t-2$	0.010	0.001	0.003
	(0.063)	(0.062)	(0.063)
Rainfall shock, t	0.030		0.031
	(0.065)		(0.063)
Rainfall shock, $t-1$	-0.083		-0.081
	(0.071)		(0.070)
Rainfall shock, $t-2$	-0.104*		-0.106*
	(0.058)		(0.058)
Commodity price shock, t		0.087	0.085
		(0.075)	(0.074)
Commodity price shock, $t-1$		-0.011	-0.015
		(0.091)	(0.092)
Commodity price shock, $t-2$		0.080	0.084
		(0.062)	(0.062)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	723	723	723
R^2	0.058	0.058	0.063

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

2.6.6 Small Conflict, Large Conflict and Conflict Onset

Our main dependent variable, the incidence of civil conflict, refers to the onset new civil conflicts and the continuation of already existing conflicts that have resulted in at least 25 battle related deaths. In this section, we first examine if the effect of RER misalignment depends on the scale of the conflict. We consider small scale civil conflict as conflict that has resulted in 25-1000 battle related deaths, and large scale civil conflict as conflict that has resulted in more than 1000 deaths.

In Columns (1)-(2) of Table 2.13, we find that RER misalignment is statically insignificant for small scale conflict. By contrast, for large scale conflict, Columns (3)-(4) show the effect of RER misalignment is positive and statistically significant. This suggests that the effect of RER misalignment on conflict comes mainly from the association between RER misalignment and large conflicts, not small conflicts. Besides the scale of the conflict, we consider the onset of new civil conflict with at least 25 deaths in sub-Saharan Africa. Civil conflict onset is defined as the year where the conflict has first started. In Column (5)-(6), we find that RER misalignment is statistically insignificant for civil conflict. At face value, we may conclude that RER misalignment mainly affects the continuation (i.e. persistence) of conflicts instead of causing new conflicts to start.[17]

[17] The statistically insignificant response of civil conflict onset could also be related to the way civil conflict onset is defined. In Fearon and Laitin (2003), Miguel et al. (2004), Ciccone (2011) and Ciccone (2013), which we follow, conflict onset is a dummy variable coded as one for the first year of a conflict episode, zero for the subsequent years of the same conflict episode and when there is no conflict. If RER misalignment affects both conflict onset and conflict persistence, it would be associated with both ones and zeros contained in the conflict onset dummy. This may cause the statistical association between RER misalignment and the conflict onset dummy to be ambiguous, and therefore insignificant, not because there is no association between RER misalignment and conflict onset, but because of the way the civil conflict onset dummy is defined.

Table 2.13: The Effect of RER Misalignment on Small Scale Conflict, Large Scale Conflict, and Conflict Onset

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Incidence of small scale conflict		Incidence of large scale conflict		Onset of civil conflict	
RER Misalignment	0.056	0.051	0.079**	0.070*	-0.000	-0.005
	(0.037)	(0.042)	(0.037)	(0.037)	(0.008)	(0.008)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
Constant	0.120***	0.148***	0.086***	0.059	0.019***	-0.000
	(0.001)	(0.053)	(0.001)	(0.037)	(0.000)	(0.004)
N	1076	1076	1076	1076	1076	1076
R^2	0.004	0.053	0.013	0.061	0.000	0.035

Note: Robust standard errors clustered at the country level are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.7 Conclusion

In developing countries, the misalignment of the real exchange rate is a common empirical phenomenon. For policy makers, this is a concern as RER misalignment may reduce economic growth. Recognizing that lower growth may lead to conflict, we investigate if RER misalignment can explain civil conflict incidence in the SSAs. To do so, we construct an RER misalignment index and find that RER misalignment is statistically significant for the incidence of civil conflict in the SSAs, where a one-standard deviation increase (i.e. overvaluation) in the RER is associated with a 4 percentage points increase in the probability of civil conflict on average. This effect is observed even after we control for rainfall and commodity price shocks – two widely acknowledged factors of civil conflict – and a battery of robustness checks. We conclude that RER misalignment, through its negative impact on growth, can explain the incidence of civil conflict in the SSAs beyond the effects of negative rainfall and commodity price shocks. Therefore, from a policy perspective, not only does stabilizing the real exchange rates of the SSAs have economic benefits, it may also contribute to political stability in the region by helping to reduce conflict. Hence, other than stabilizing the RER, it is important for central banks to manage and ensure that RER is not overvalued.

References

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque Country. *The American Economic Review 93*(1), 113–132.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?

Bates, R. H. (2008). State failure. *Annual Review of Political Science development policy 11*, 1–12.

Bazzi, S. and C. Blattman (2014). Economic shocks and conflict: Evidence from commodity prices. *American Economic Journal: Macroeconomics 6*(4), 1–38.

Blackburne, E. F. and M. W. Frank (2007). Estimation of nonstationary heterogeneous panels. *Stata Journal 7*(2), 197.

Blattman, C. and E. Miguel (2010). Civil war. *Journal of Economic literature 48*(1), 3–57.

Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*(1), 115–143.

Brückner, M. and A. Ciccone (2010). International commodity prices, growth and the outbreak of civil war in Sub-Saharan Africa. *The Economic Journal 120*(544), 519–534.

Burke, M. B., E. Miguel, S. Satyanath, J. A. Dykema, and D. B. Lobell (2009). Warming increases the risk of civil war in Africa. *Proceedings of the national Academy of sciences 106*(49), 20670–20674.

Chassang, S. and G. Padro-i Miquel (2009). Economic shocks and civil war. *Quarterly Journal of Political Science 4*(3), 211–228.

Chinn, M. D. (2006). A primer on real effective exchange rates: determinants, overvaluation, trade flows and competitive devaluation. *Open Economies Review 17*(1), 115–143.

Ciccone, A. (2011). Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics 3*(4), 215–227.

Ciccone, A. (2013). Estimating the effect of transitory economic shocks on civil conflict. *Review of Economics and Institutions 4*(2), 14.

Collier, P. (2008). *The bottom billion: Why the poorest countries are failing and what can be done about it.* Oxford University Press, USA.

Collier, P. and A. Hoeffler (1998). On economic causes of civil war. *Oxford Economic Papers 50*(4), 563–573.

Cottani, J. A., D. F. Cavallo, and M. S. Khan (1990). Real exchange rate behavior and economic performance in LDCs. *Economic Development and Cultural Change 39*(1), 61–76.

Darvas, Z. (2012). Real effective exchange rates for 178 countries: a new database.

De Ree, J. and E. Nillesen (2009). Aiding violence or peace? the impact of foreign aid on the risk of civil conflict in sub-Saharan Africa. *Journal of Development Economics 88*(2), 301–313.

Deaton, A. (1999). Commodity prices and growth in Africa. *The Journal of Economic Perspectives 13*(3), 23–40.

Deaton, A., R. I. Miller, et al. (1995). *International commodity prices, macroeconomic performance, and politics in Sub-Saharan Africa.* International Finance Section, Department of Economics, Princeton University.

Eck, K. and L. Hultman (2007). One-sided violence against civilians in war: Insights from new fatality data. *Journal of Peace Research 44*(2), 233–246.

Edwards, S. (1989). Exchange rate misalignment in developing countries. *The World Bank Research Observer 4*(1), 3–21.

Elbadawi, I. A. et al. (1998). Real exchange rate policy and non-traditional exports in developing countries.

Elbadawi, I. A., L. Kaltani, and R. Soto (2012). Aid, real exchange rate misalignment, and economic growth in sub-Saharan Africa. *World Development 40*(4), 681–700.

Fearon, J. D. and D. D. Laitin (2003). Ethnicity, insurgency, and civil war. *American Political Science Review 97*(01), 75–90.

Forbes, K. J. and F. E. Warnock (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics 88*(2), 235–251.

Freund, C. and M. D. Pierola (2012). Export surges. *Journal of Development Economics 97*(2), 387–395.

Ghura, D. and T. J. Grennes (1993). The real exchange rate and macroeconomic performance in sub-Saharan Africa. *Journal of Development Economics 42*(1), 155–174.

Goldfajn, I. and R. Valdes (1999). The aftermath of appreciations. *Quarterly Journal of Economics 114*(229), 62.

Goldstone, J. A., R. H. Bates, D. L. Epstein, T. R. Gurr, M. B. Lustik, M. G. Marshall, J. Ulfelder, and M. Woodward (2010). A global model for forecasting political instability. *American Journal of Political Science 54*(1), 190–208.

Grossman, H. I. (1991). A general equilibrium model of insurrections. *The American Economic Review*, 912–921.

Habib, M. M., E. Mileva, and L. Stracca (2017). The real exchange rate and economic growth: revisiting the case using external instruments. *Journal of International Money and Finance 73*, 386–398.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the influence of climate on human conflict. *Science 341*(6151), 1235367.

Hull, P. and M. Imai (2013). Economic shocks and civil conflict: Evidence from foreign interest rate movements. *Journal of Development Economics 103*, 77–89.

Janus, T. and D. Riera-Crichton (2015). Economic shocks, civil war and ethnicity. *Journal of Development Economics 115*, 32–44.

Krueger, A. (1998). Why trade liberalization is good for growth. *The Economic Journal 108*(450), 1513–1522.

Lane, P. R. and F. G. Milesi (2007). The external wealth of nations mark ii: Revised and extended estimates of foreign assets and liabilities, 1970–2004. *Journal of International Economics 73*(2), 223–250.

MacDonald, R. (2000). Concepts to calculate equilibrium exchange rates: an overview.

Magee, C. S. and T. G. Massoud (2011). Openness and internal conflict. *Journal of Peace Research 48*(1), 59–72.

Marshall, M. G. and K. Jaggers (2009). Polity IV project: Dataset user's manual center for global policy, school of public policy, George Mason University and Center for Systemic Peace.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy 112*(4), 725–753.

Montiel, P. J. (1999). The long-run equilibrium real exchange rate: Conceptual issues and empirical research. *Exchange rate misalignment: Concepts and measurement for developing countries*, 219–263.

Nouira, R. and K. Sekkat (2012). Desperately seeking the positive impact of undervaluation on growth. *Journal of Macroeconomics 34*(2), 537–552.

Nunn, N. and N. Qian (2014). US food aid and civil conflict. *The American Economic Review 104*(6), 1630–1666.

Nurkse, R. (1945). *Conditions of international monetary equilibrium.* International Finance Section, Department of Economics and Social Institutions, Princeton University.

Pesaran, M. H., Y. Shin, and R. P. Smith (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association 94*(446), 621–634.

Pesaran, M. H. and R. Smith (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics 68*(1), 79–113.

Pettersson, T. and P. Wallensteen (2015). Armed conflicts, 1946–2014. *Journal of Peace Research 52*(4), 536–550.

Pick, D. H. and T. L. Vollrath (1994). Real exchange rate misalignment and agricultural export performance in developing countries. *Economic Development and Cultural Change 42*(3), 555–571.

Raleigh, C. and H. Hegre (2009). Population size, concentration, and civil war. a geographically disaggregated analysis. *Political Geography 28*(4), 224–238.

Rodrik, D. (2008). The real exchange rate and economic growth. *Brooking Papers on Economic Activity 2008*(2), 365–412.

Savun, B. and S. Cook (2010). Exogenous shocks, bargaining problems, and the onset of civil war. In *American Political Science Association Annual Meeting*.

Schröder, M. (2013). Should developing countries undervalue their currencies? *Journal of Development Economics 105*, 140–151.

Sekkat, K. (2016). Exchange rate misalignment and export diversification in developing countries. *The Quarterly Review of Economics and Finance 59*, 1–14.

Sekkat, K. and A. Varoudakis (2000). Exchange rate management and manufactured exports in sub-Saharan Africa. *Journal of Development Economics 61*(1), 237–253.

Williamson, J. (1990). What Washington means by policy reform. *Latin American adjustment: How much has happened 1*, 90–120.

Appendix A: List of Sample Countries, Data Sources and Descriptive Statistics

Table A1: List of Countries in the Sample

Angola	Benin	Botswana	Burundi
Cabo Verde	Cameroon	Central African Republic	Chad
Congo, Dem. Rep.	Congo, Rep.	Cote d'Ivoire	Equatorial Guinea
Ethiopia	Gabon	Gambia, The	Ghana
Guinea-Bissau	Kenya	Lesotho	Madagascar
Malawi	Mali	Mauritania	Mauritius
Mozambique	Namibia	Niger	Nigeria
Rwanda	Senegal	South Africa	Sudan
Togo	Uganda	Zambia	

Note: The sample period extends from 1975-2006. Due to real exchange rate data unavailability for some countries, the study is restricted to 35 SSAs.

Table A2: Data Sources and Definitions

Variable Name	Definitions	Data sources
Real effective exchange rate	CPI based REER constructed based on the weights of 67 trading partners. An increase in the index indicates appreciation, which corresponds to a loss of competitiveness.	Darvas (2012)
Productivity (Balassa-Samuelson effect)	The ratio of GDP per capita (home country) to the OECD average of GDP per capita income at current prices	WDI (2016)
Net foreign asset position (NFA)	NFI is the ratio of net foreign assets relative to GDP at current prices	Lane and Milesi (2007)
Government expenditure	General government final consumption expenditure (% of GDP)	WDI (2016) (complemented by IFS data for Cabo Verde, Ethiopia, Nigeria, Tanzania and Zambia)
Terms of trade	Net barter terms of trade index is calculated as the percentage ratio of the export unit value indexes to the import unit value indexes, measured relative to the base year 2000.	WDI (2016)
Trade openness	Ratio of export and import to gross domestic product	WDI (2016) (complemented by IFS data for Ethiopia and Zambia)
GDP per capita	GDP per capita is gross domestic product divided by population in constant 2005 US$	WDI (2016)
RER misalignment	Percentage difference between real effective exchange rate and its estimated equilibrium value	Authors' calculation based on REER data from Darvas (2012)
International interest rate	Proxy by US 3-Month Treasury Bill	IFS CD-ROM
Foreign Aid	Official development assistance as a share of GDP	WDI (2016)
Inflation rate	Consumer prices (annual %), used as a proxy for domestic macroeconomic policy	WDI(2016)
Export (% of GDP)	Exports of goods and services (% of GDP)	WDI (2016)

Table A3: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Misalignment	1086	0.029	0.333	-1.787	1.896
Incidence of civil conflict	1226	0.213	0.410	0	1
Inflation rate	1004	59.48	784.0	-17.64	23773
Commodity price growth (shocks)	789	0.028	0.210	-0.482	1.251
Rainfall level	789	969.0	481.3	96.11	2073
Rainfall growth (shocks)	789	0.021	0.210	-0.547	1.677
Terms of trade	1260	115.7	43.54	21.40	357.6
Government expenditure	1260	15.67	8.348	0	84.51
Foreign aid (% of GDP)	1260	11.59	11.56	-0.253	94.95
Trade openness	1260	70.50	49.32	0.046	531.7
GDP per capita	1163	1187	1825	113.7	13706
Intermediate institution	1260	0.264	0.441	0	1
Net foreign asset (% of GDP)	1260	-0.739	0.869	-5.410	10.10
International interest rate	1120	6.090	2.944	1.021	14.35
Gross saving (% of GDP)	1089	8.784	23.39	-241.9	84.78
Deposit rate	884	9.279	9.178	2	147.1
Net capital inflow	1142	0.049	0.707	-3.719	6.857
De jure capital account openness	1164	-0.873	0.838	-1.904	2.374
World capital flows	1260	1490	2050	48.50	9200
Export (% of GDP)	1310	30.64	19.17	2.52	124.39

Note that the world capital flows are in billion U.S. dollars.

Appendix B: Mean Group, Pooled Mean Group and the Dynamic Fixed Effects Estimator

In this appendix, we provide some further discussion on the Mean Group, Pooled Mean Group and Dynamic Fixed Effects estimators that were employed to estimate the real exchange rate model in Eq. (2.3) of Section (A.). In general, for the panel of N countries and T time periods, we may model the real exchange rate model as an autoregressive distributive lag (ARDL) process with p lags for the real exchange rate and q lags for the different real exchange rate fundamentals,[18]

$$RER_{it} = \sum_{j=1}^{p} \lambda_{ij} RER_{i,t-j} + \sum_{j=0}^{q} \boldsymbol{\delta}'_{ij} \mathbf{X}_{i,t-j} + \mu_i + \varepsilon_{it} \tag{2.11}$$

where RER_{it} is the real effective exchange rate, $\mathbf{X}_{it}$ is a 7×1 vector of the real exchange rate fundamentals that include the terms of trade, net foreign asset, international interest rate, foreign aid, productivity, government expenditure, and trade openness (see Section (2.3.2)). The parameter λ_{ij} represents the coefficient on the j^{th} lagged of RER_{it}, $\boldsymbol{\delta}_{ij}$ represents a 7×1 vector of coefficients on the j^{th} lagged of the RER fundamentals, μ_i is the country fixed effect and ε_{it} is a white noise.

In non-stationary heterogeneous panel data models, the common procedure of estimating Eq. (2.11) is to re-parametrize it into an error correction form:

$$\triangle RER_{it} = \phi_i (RER_{i,t-1} - \beta'_i \mathbf{X}_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \triangle RER_{i,t-1} + \sum_{j=0}^{q-1} \boldsymbol{\delta}^{*\prime}_{ij} \triangle \mathbf{X}_{i,t-j} + \mu_i + \varepsilon_{it} \tag{2.12}$$

where $\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im}$ for $j = 1, 2, ..., p-1$, $\boldsymbol{\delta}^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im}$ for $j = 1, 2, ..., q-1$, and $\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$ is the error-correcting speed of adjustment term. If $\phi_i = 0$, there is no long-run relationship between the model variables. If $\phi_i < 0$, any short-run deviation of the variables from their equilibrium relationship will return to zero in the long run. The set of parameters $\beta_i = \sum_{j=0}^{q} \delta_{ij} / (1 - \sum_k \lambda_{ik})$

[18]Following Pesaran et al. (1999), the lag length order of of RER_{it} and $\mathbf{X}_{i,t}$ are determined by the Schwarz Bayesian information criterion (SBIC) where the maximum lag length is set to be 1. As Pesaran et al. (1999) also clearly demonstrated, the estimated parameters of the mean group and the pooled mean group procedures are robust to the choice of the lag length order if T is sufficiently large.

represents the long-run coefficients. These parameters, also known as cointegrating parameters, capture the long-run relationships between the variables in the model.

In Section (A.), we have applied three estimation techniques to estimate Eq. (2.12), which are common in the dynamic heterogeneous panel literature (Pesaran and Smith, 1995; Pesaran et al., 1999; Blackburne and Frank, 2007). The first approach is the Dynamic Fixed Effect estimator. This approach pools the time-series data of each country and assumes that the long-run parameters, the short parameters and the error variances are the same across countries. The only parameters that may vary across countries are the intercepts (Blackburne and Frank, 2007).

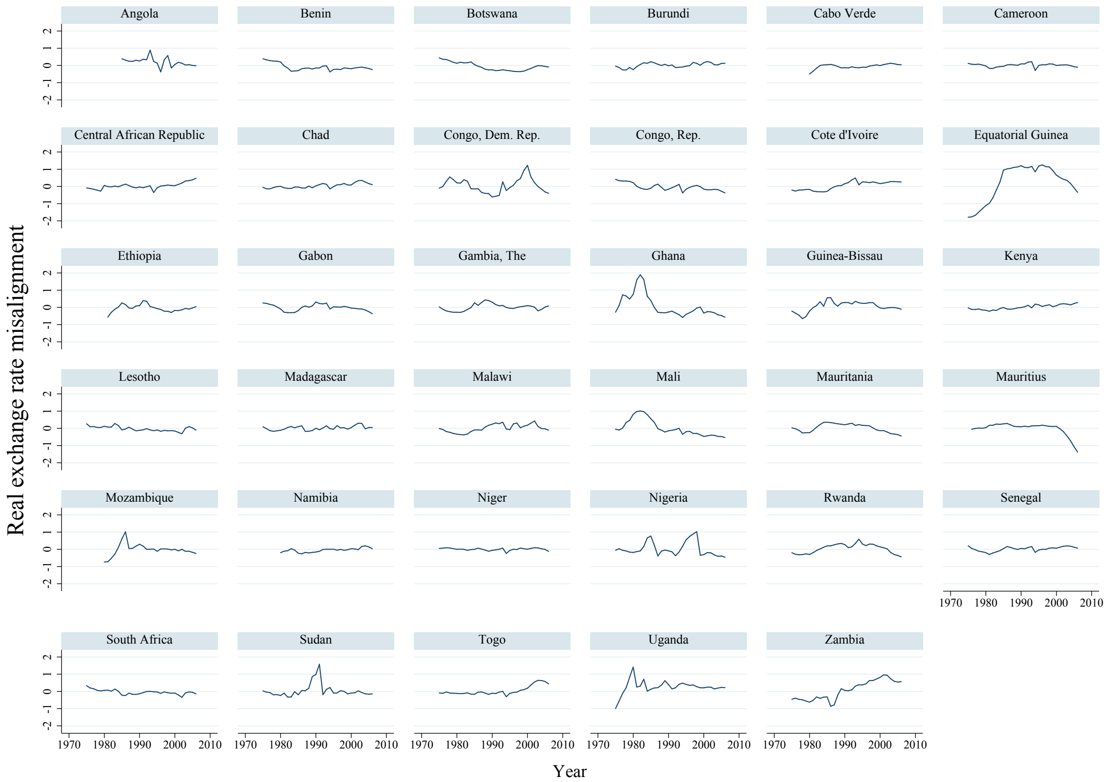
The second approach is the Mean Group estimator of Pesaran and Smith (1995). This approach assumes that the intercepts, the long-run parameters, the short-run parameters and the error variances are potentially different for each country in the panel. Therefore, concerning Eq. (2.12), the Mean Group estimator will estimate this model for each country, and then average up the country-specific estimates.

The third approach is the Pooled Mean Group estimator of Pesaran et al. (1999). This approach lies in between the Dynamic Fixed Effects and the Mean Group estimators in terms of allowing for model heterogeneity. Specifically, the Pooled Mean Group estimator allows the short-run parameters and error variances to potentially vary across countries, just as the Mean Group estimator does, although not the Dynamic Fixed Effects estimator. However, the Pooled Mean Group estimator holds the long-run cointegrating vectors fixed, which is what the Dynamic Fixed Effects estimator does, but not the Mean Group estimator.

As such, in terms of allowing the parameters to vary, the Mean Group estimator is the most flexible while the Dynamic Fixed Effects estimator is the least flexible. If the short and long-run parameters and the error variances are different across countries, fixing any of these will yield inconsistent estimates. However, if these parameters and error variances are identical, assuming otherwise will yield inefficient estimates (Blackburne and Frank, 2007). Thus, in our paper, we adopt the Pooled Mean Group estimator, which combines both pooling and averaging, and thus provides the best compromise between consistency and efficiency.

Appendix C: The Misalignment Index for Individual Countries

Figure 2.3: RER Misalignment Index for Each SSA Countries in the Sample



Appendix D: Export as a Percentage of GDP for Individual Countries

Figure 2.4: Export as a % of GDP for Each SSA Countries in the Sample

Chapter 3

Does non-U.S. Emergency Food Aid Increase Civil Conflict in the Recipient Countries?

Dessie Tarko Ambaw

School of Economics, The University of Adelaide

Statement of Authorship

Title of Paper	Does non-U.S. Emergency Food Aid Increase Civil Conflict in the Recipient Countries?
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	The paper is written in publication style for submission to a journal.

Principal Author

Name of Principal Author (Candidate)	Dessie Tarko Ambaw		
Contribution to the Paper	This paper is written by a sole author (the candidate).		
Overall percentage (%)	100%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the sole of author of this paper.		
Signature		Date	06/09/2018

Abstract

Through the United States Agency for International Development (USAID), the U.S. is the largest provider of food assistance to poor countries that are facing a hunger crisis or are affected by disasters. While the intention of USAID is noble, recent studies have shown that U.S. *emergency* food aid has partly contributed in the rise of civil conflict in conflict-prone recipient countries because it has been looted or stolen in exchange for arms. In this paper, we show that *non-U.S.* emergency food aid does not have a statistically significant effect on civil conflict in sub-Saharan Africa (SSA). To address the potential endogeneity of food aid allocation that biases OLS estimates, we employ the number of affected people by the natural disasters *in the other* sub-Saharan Africa countries as an instrument for emergency food aid. Unlike the previous literature, we find that non-emergency food aid has no a statistically significant effect on increasing civil conflict in the region suggesting non-U.S. food aid is still an important international development policy tool to fight hunger and suffering in developing countries.

Key Words: Food Aid, Civil Conflict, Instrumental Variable Estimation, sub-Saharan Africa

JEL Codes: D74, F35, H84, O19, Q11, Q18

3.1 Introduction

Although emergency food assistance has helped to alleviate hunger and malnutrition, critics are concerned that it may also lead to increased conflict in conflict-prone regions such as sub-Saharan Africa (SSA). Humanitarian aid, for example, could be intercepted by militias to support insurgency and therefore foster conflict. However, empirical evidence that food aid leads to more conflict has been tenuous at best. In a recent study, Nunn and Qian (2014) found that U.S. food aid could increase civil conflict in a large sample of aid-receiving developing countries. Concerned that this effect could be driven by specific countries, Chu et al. (2017) then replicated Nunn and Qian's (2014) and show that food aid has a homogeneous effect on conflict across countries, which suggests that Nunn and Qian's (2014) findings are robust. However, using a different empirical approach, USAID (2014) and Christian and Barrett (2017) showed that that U.S. food aid was not statistically significant at all, which raises the question on whether food aid has a quantitatively important impact on conflict.[1]

Empirically, it is difficult to identify the effect of food aid on conflict as the allocation of food aid is likely to be endogenous. Firstly, food aid is endogenous as there is a tendency for aid agencies to allocate more food aid to conflict-prone regions. Thus, conflict might influence food aid. Secondly, there could be common factors (such as the occurrence of economic crisis) that drive both conflict and food aid in the same direction. Thus, the empirical association between food aid and conflict could coincidental. Finally, food aid data is likely to contain measurement error. If this error is classical, the least squares estimates of the effect of food aid on conflict would be attenuated.

As an identification strategy, Nunn and Qian (2014) developed a Bartik-style (Bartik, 1991) instrumental variable (IV) for contemporaneous U.S. wheat aid. The Bartik IV typically interacts a time-varying macroeconomic factor, which plays the

[1]The sample countries considered in USAID (2014) and Christian and Barrett (2017) are exactly similar to Nunn and Qian (2014). However, the former two paper extends Nunn and Qian (2014) in different ways. For example, USAID (2014) excludes the 1970-1973 data and controls additional variables. Christian and Barrett (2017) also argue that the non-parallel trend problem may cause the exclusion restriction assumption in Nunn and Qian (2014) to be violated. As such, using placebo, randomization inference, and Monte Carlo simulation tests, they find that food aid does not have any statistical significant effect on conflict.

role of a treatment variable, with a country-specific cross-sectional exposure to that factor, which measures treatment intensity. In Nunn and Qian (2014), the Bartik IV is constructed by interacting the amount of U.S. wheat aid in the previous year (the macroeconomic factor) with each country's propensity of receiving U.S. wheat aid (the cross-country exposure variable). Concerns about the endogeneity of the Bartik IV usually arise because the exposure variable could be correlated with the unobserved country heterogeneity. This issue, as Nunn and Qian (2014) argued, could be dealt with by using country fixed effects. However, Christian and Barrett (2017) countered that their Bartik IV might still be invalid: if there are non-linear and non-parallel trends in the cross-sectional exposure variable, the use of fixed effects might be insufficient (see, also, Bazzi and Clemens, 2013).

Thus, while Bartik IVs are easy to construct, there are issues concerning their validity that cannot be easily addressed. In this paper, we propose a new *non-Bartik* IV to estimate the causal effect of emergency food aid from Development Assistant Committee (DAC) countries on the civil conflict of SSA countries. To construct our instrument for the emergency food aid of the SSA country in question, we use information related to natural disasters that have occurred in the other SSA countries. These include geophysical disasters (such as earthquake and volcanic eruption), meteorological disasters (storm and extreme temperature), hydrological disasters (flood and landslide), climatological disasters (drought and wildfire) and biological disasters (epidemic and insect infestation). The occurrence of natural disasters is exogenous. When some countries are struck with natural disasters, food aid could be diverted away from non-affected countries, especially if these disasters affect a large number of people. As such, to identify the effect of food aid, we exploit the exogenous variation in a country's food aid associated with the number of natural disaster affected people in foreign countries.[2] Our identification strategy, therefore, relies on the assumption that controlling for the relevant observables, the number of disaster-affected people in foreign countries only affects civil conflict in the domestic

[2]The emergency database (EM-DAT) defines the number of affected people as "People requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance".

country through its effect on the emergency food aid the latter receives.

Based on a panel of 30 SSA countries from 1995 to 2015, we find that emergency food aid does not have a statistically significant effect on the incidences of civil conflict (small scale conflict) and civil war (large scale conflict). Thus, the argument that increasing the quantity of food aid to war torn developing countries increases the capability of rebel groups to fight the state may not be true for non-U.S. DAC countries emergency food aid to SSA. Our baseline results are not dependent on whether spatial and temporal conflict spillovers are accounted for in the model. Additional, we find our results to be robust in a battery of other sensitivity checks.

There is now a large literature that looks at the effectiveness of foreign aid for economic development in developing countries, which our paper is related to. For example, Bourguignon and Sundberg (2007), Crost et al. (2014) and Galiani et al. (2017) studied the effect of aid on economic growth and civil conflict and their findings, taken together, are not conclusive about whether aid may either reduce or improve economic outcomes. Our paper is related to the literature by focusing on the effect of emergency food aid on civil conflict. Methodologically, our paper is related to recent research that uses exogenous shocks to construct an instrument for aid. For example, Werker et al. (2009) employed oil price shocks to study the effect of oil-rich donor countries aid on the economic growth of aid recipient developing countries, but found that foreign aid did not have significant effects on growth. Similarly, Nunn and Qian (2014) constructed their Bartik IV for aid, and found that U.S. wheat aid increases the incidence of conflict in a large set of food aid recipient developing countries. Our study contributes to the literature by proposing a novel, non-Bartik IV for food aid, which is driven by exogenous shocks arising from natural disasters.

The reminder part of the paper is organized as follows. Section 3.2 outlines the data and the summary statistics of the study. Section 3.3 lays out the empirical strategy of the paper. In section 3.4, we present the results of the study. Finally, section 3.5 concludes.

3.2 Data

Our dataset covers 30 sub-Saharan African emergency food aid recipient countries for the period between 1995 and 2015. In this section, we will first describe the dependent and explanatory variables used in the paper. Next, we will discuss how our instrumental variable (IV) is constructed. Finally, we will present the descriptive statistics and explore some data visualization.

Civil conflict: The data on civil conflict comes from the Uppsala Conflict Data Program (UCDP) armed conflicts dataset. UCDP defines civil conflict as conflict involving government or territory or both where the use of armed force between two parties results in 25 or more battle-related deaths. The study focuses exclusively on internal armed civil conflict, which is defined as "conflict (that) occurs between the government of a state and one or more internal opposition group(s) without intervention from other states" (Pettersson and Wallensteen, 2015, p.9).

The first main dependent variable of the study is the incidence of civil conflict. The incidence of civil conflict is an indicator variable which equals to 1 if there is conflict with 25-1000 battle related deaths in a given country during a given year. The second dependent variable of the study is civil war incidence which is an indicator variable that equals to 1 if there is conflict with more than 1000 battle related deaths in a country for a given time period and zero otherwise (Miguel et al., 2004; Nunn and Qian, 2014).

Emergency food aid: Our data on emergency food aid data is taken from the OECD Stat database. We consider the emergency food aid data from Development Assistant Committee (DAC) countries of the Organization of Economic Cooperation and Development (OECD) except U.S. food aid. In other words, we focus on the 29 DAC countries, which excludes the U.S.[3] OECD stat database documents the emergency food aid value in terms of million U.S. dollars.

[3]The list of the 29 DAC countries are presented in Table A1 of the appendix.

Natural disaster: The natural disaster data comes from the emergency event database (EM-DAT), which is established by the Centre for Research on the Epidemiology of Disasters (CRED). The number of people affected by natural disasters is the information we use for constructing the instrument for emergency food aid (see Section 3.3 for more details). However, other control variables such as total number of deaths, total homeless and total resource damage are also extracted from the EM-DAT website. The study employs the number of natural disaster affected people in foreign countries as an instrument (IV) for emergency food aid to estimate its effect on civil conflict in food aid recipient countries. According to EM-DAT, the natural disasters that are considered for computing the number of disaster affected people include earthquake, volcanic eruption, extreme temperature, storm, flood, landslide, drought, wildfire, epidemic, and insect infestation.

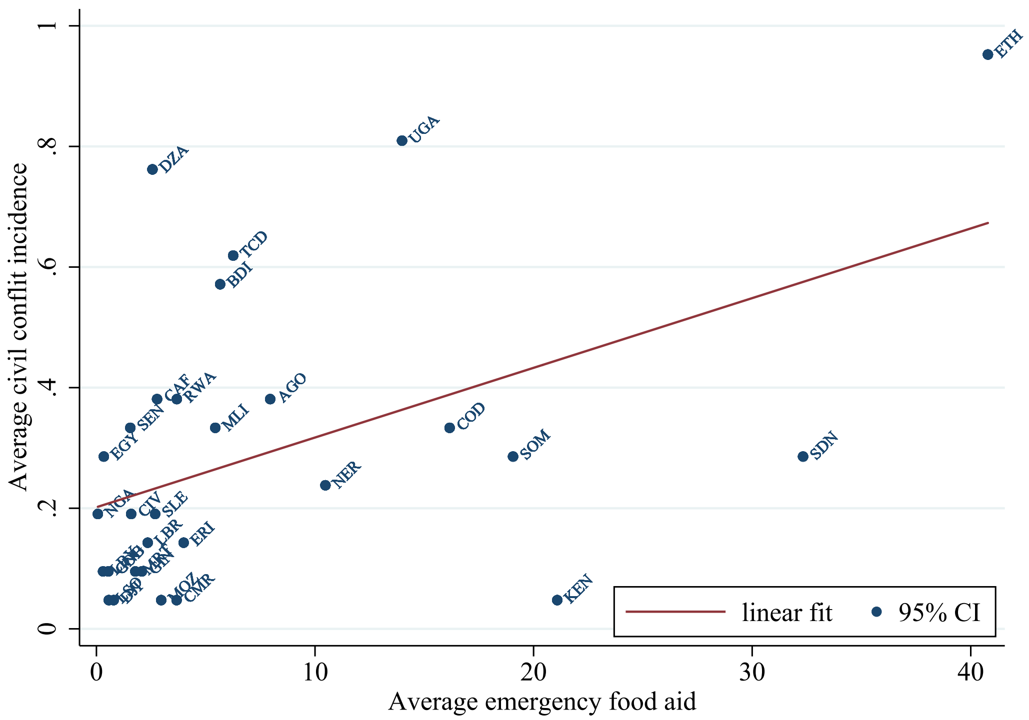
Table 3.1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Civil conflict incidence	630	0.284	0.451	0	1
Civil war incidence	630	0.09	0.287	0	1
Affected people	630	339057.61	1435932.155	0	23000000
Homeless	630	4555.008	23094.698	0	282975
Total Damage	630	14681.481	204709.265	0	5000000
Total deaths	630	186.289	928.349	0	20011
Emergency food aid from DAC	630	7.133	15.175	0	147.685

Table 3.1 presents the summary statistics of the main variables. The data shows that the SSA is one of the highly conflict affected regions in the world, where civil conflict incidence occurs in the 28.4% of country-year combinations and civil war occurs in 9% the country-year combinations. Thus, Table 3.1 also reports the summary statistics for the different effects of natural disaster in the SSA countries. For example, the country-year average number of people affected and killed by natural disasters were 339,058 and 186 in the region, respectively. These figures suggest that natural disasters are one of the major causes of human suffering in sub-Saharan African countries. Moreover, more than 7 million USD average emergency food aid is given to the SSA from the 29 DAC countries due to natural disasters.

To first explore the association between conflict and emergency food aid, we first visualized their scatter plots. Figure 3.1 plots the relationship between small scale

Figure 3.1: Civil Conflict Incidence and Emergency Food Aid in the SSA

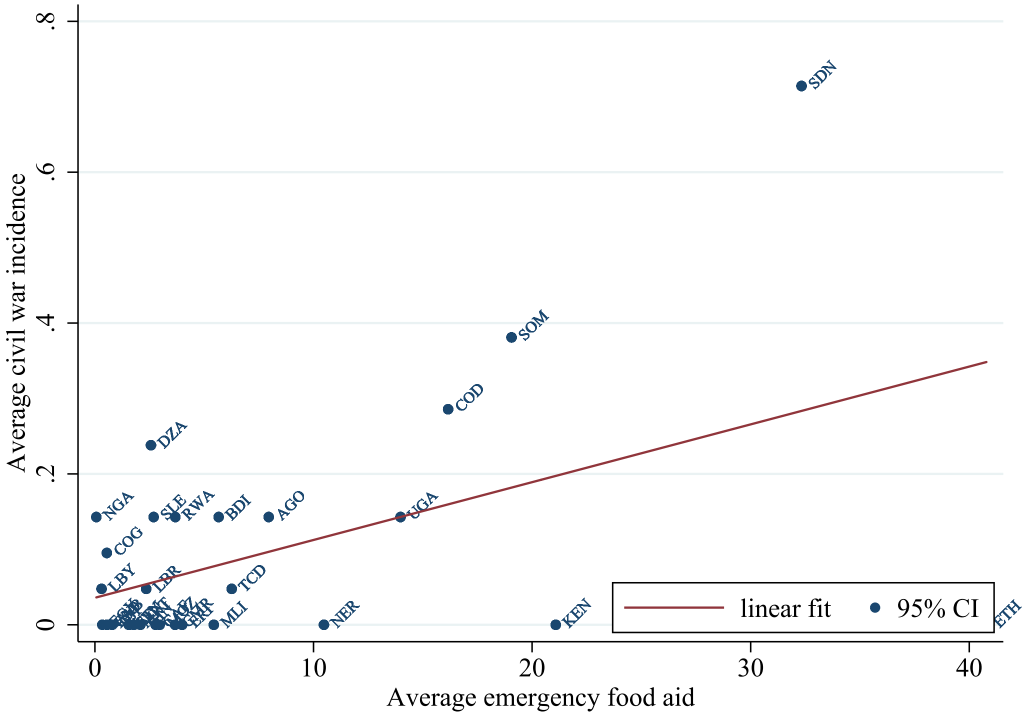


Note: This figure plots the average civil conflict incidence and the average value of emergency food aid in the 30 sample SSA countries.

civil conflict incidence and DAC emergency food aid to the region. Here, we can see that higher levels of emergency food aid are associated with greater civil conflict incidence in the SSA.

This positive association is also consistent with Figure 3.2, which shows that civil war incidence and emergency food aid are positively correlated in the SSA. Finally, we provide a simple scatter plot of emergency food aid and the number of natural disaster affected people in other SSA countries to explore the relationship between disaster casualties and the allocation of emergency food aid in the region. As Figure 3.3 shows, notwithstanding a few outlying countries (such as Sudan), an increase in the number of natural disaster affected people in the foreign country is strongly negatively associated with the shipment of food aid to a given SSA country. Thus, the severity of natural disasters in foreign countries, reflected by the number of people affected by these disasters, could cause food aid to be diverted away from the domestic aid recipient.

Figure 3.2: Civil War Incidence and Emergency Food Aid in the SSA



Note: This figure plots the average civil war incidence and the average emergency food aid in the 30 sample SSA countries.

3.3 Methodology

To identify the causal effect of emergency food aid on conflict, we estimate the following equations with the two stage least square (2SLS) approach:[4]

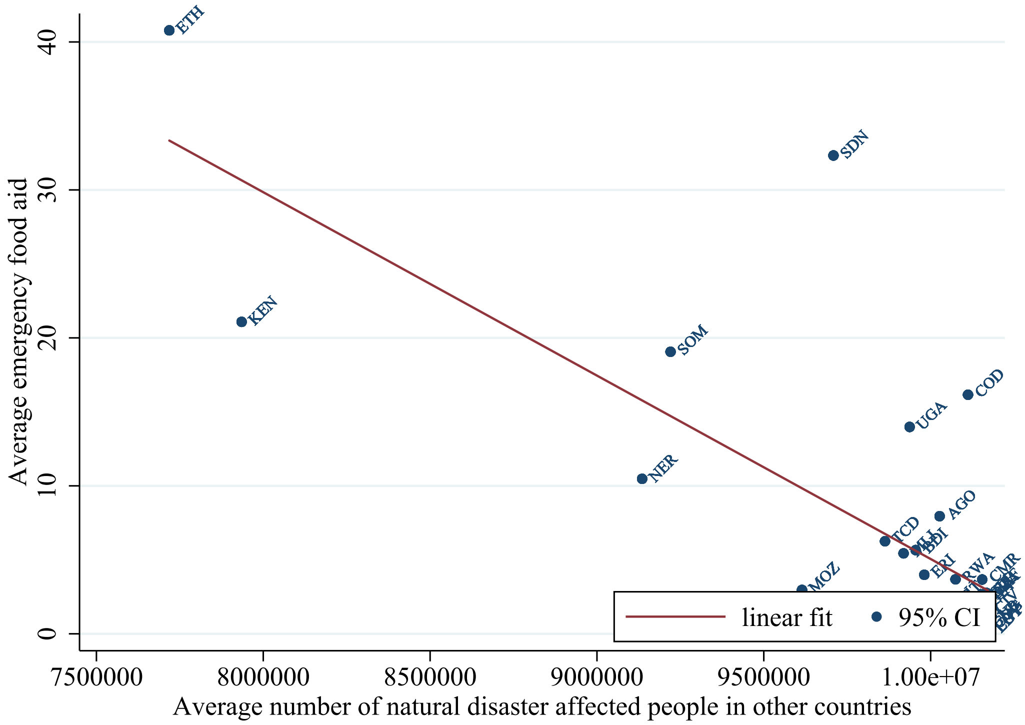
$$Conflict_{it} = \beta(FoodAid)_{it} + X_{it}\Gamma + \varphi_t + \psi_i + \mu_{it} \tag{3.1}$$

$$FoodAid_{it} = \alpha(ForeignAffected)_{it} + X_{it}\Gamma + \varphi_t + \psi_i + \varepsilon_{it} \tag{3.2}$$

where $Conflict_{it}$ is an indicator variable which equals 1 if there is conflict with 25-1000 battle related deaths in country i during year t. $FoodAid_{it}$ is the value of emergency food aid (the endogenous variable) from DAC countries. $ForeignAffected_{it}$ is the number of people affected by natural disasters in other SSA countries. φ_t and ψ_i denote the year and country fixed effects; while μ_{it} and ε_{it} are the error terms for the second and the first stage equations of the 2SLS system, respectively.

[4]Implicitly we have used the linear probability model (LPM) to estimate Eq. (3.1) as it allows to control for unobserved country characteristics that may lead a country to be more conflict-prone. Moreover, the LPM approach suitable to simplify the interpretation of the estimated coefficients.

Figure 3.3: The Number of People Affected by Natural Disaster *in Other Countries* and Emergency Food Aid in the SSA



Note: This figure plots the average value of emergency food aid and the average number of natural disaster affected people in other SSA countries.

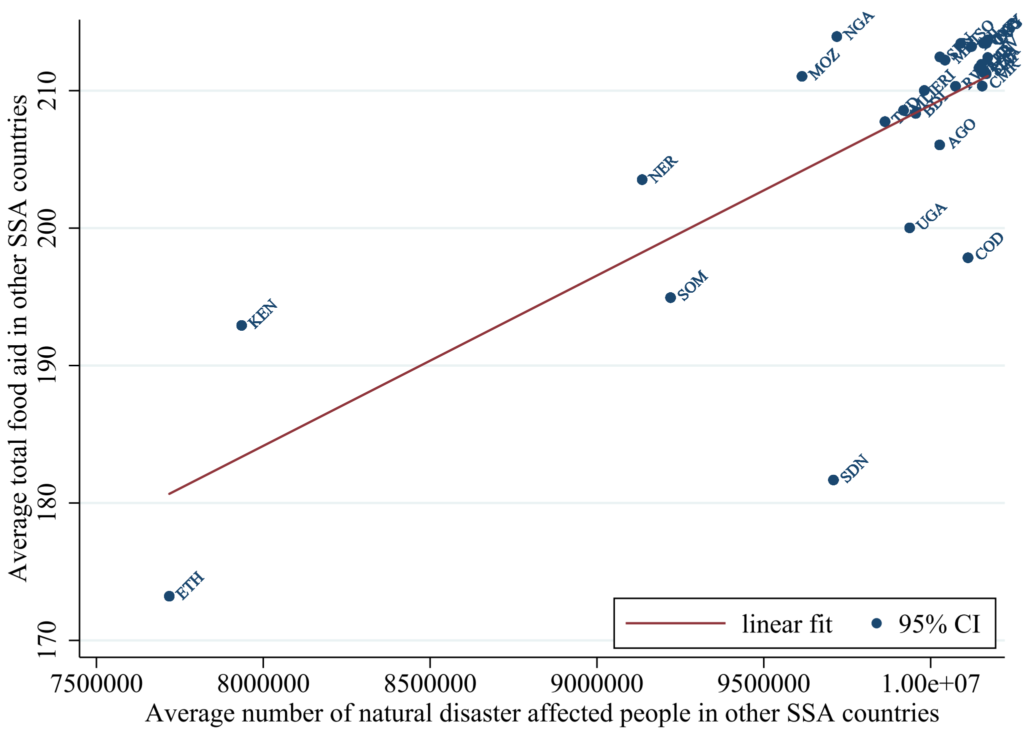
We also re-estimate Eq. (3.1) and Eq. (3.2) with 2SLS regression using civil war incidence as the dependent variable. Civil war incidence is an indicator variable that is equal to 1 for a conflict episode resulting in more than 1000 battle related deaths in country i and year t; and 0 otherwise. This allows us to estimate the effect of emergency food aid on the incidence of large scale civil conflict. In all the specifications, we have controlled country specific time trends. Besides that Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used in the 2SLS analysis.

Potential identification concerns: We employ the 2SLS regression approach as it is difficult to identify the effect of food aid on civil conflict with the OLS estimation approach. The primary reason for this problem is reverse causality: civil conflict may increase the need for emergency food aid, implying that the relationship between food aid and conflict is bi-directional. To disentangle the causal effect of food aid on conflict, we propose to use the number of natural disaster affected people in other

SSA countries as an instrument for emergency food aid received in a country. The idea is that there is competition for food aid among these countries. Countries that are struck by natural disasters may therefore receive more aid at the expense of the unaffected SSA countries. In this regard, natural disasters in neighboring countries are negative shocks to the amount food aid a country receives.

Figure 3.4 shows the positive relationship between average number of natural disaster affected people in other SSA countries and the average food aid they receive. The positive relationship suggests that there is indeed competition for food aid among SSA countries which implies the plausibility of employing natural disaster affected people in other SSA countries as an instrument for domestic emergency food aid.

Figure 3.4: Average Food Aid and Disaster Affected People in Other Countries



Note: This figure plots the average emergency food aid in other SSA countries and the average number of natural disaster affected people in other SSA countries.

The basic exclusion restriction of the study is that the number of natural disaster affected people in the other SSA countries affects civil conflict in the home country only through the emergency food aid the latter receives. There may, nonetheless, be some concerns about the identification assumption imposed here. Firstly, some natural disasters may affect large geographical areas (i.e. more than one country).

When other countries suffer from natural disasters, the country in question may suffer from the same disasters as well. Natural disasters, however, may directly affect conflict. Therefore, to isolate the influence of natural disasters occurring in other countries from the influence of natural disasters occurring in the home country, we control for the latter, which is the number of affected people, the number of deaths and total damage in the country due to the occurrence of natural disasters.

Secondly, there could be unobserved country heterogeneity that affects both conflict and the occurrence of natural disasters in the country. For example, the location of a country – such as having rugged mountain or bad climate – may affect how disaster-prone the country is (Buhaug et al., 2009), as countries with rugged maintains could be prone to earthquakes and land slides, and those covered by desserts could be affected by heat wave or sand storms. To address the confounding influence of unobserved country heterogeneity, we employ country fixed effects. We believe this is reasonable as geographical characteristics can be treated as time invariant relative to the period of this study.

Thirdly, there could be crowding out (or crowding in) of emergency food aid on domestic crop production and food import. For instance, an increase in the quantity of emergency food aid may generate a secondary effect where domestic cereal production or food import is reduced. This crowding out effect, in turn, may in turn lead to civil conflict. Concerning this issue, we may estimate the effect of food aid on food production and food import using the number of natural disaster affected people in the other countries as an IV for food aid. The estimated coefficients of emergency food aid should be close to zero and statistically insignificant if food aid does not crowding-out (crowding-in) food production or food import, which we have found to be true (see Section 3.4.4).

Finally, food aid may also crowd-out other forms of aid (Nunn and Qian, 2014) that may increase (De Ree and Nillesen, 2009) or decrease (Grossman, 1992) the risk of civil conflict. For example, food aid may reduce other forms of aid from the 29 DAC sample countries or from the US and other non-DAC donor countries. In order to check the likelihood of such crowding-out effects, we estimate the effect of food aid on DAC countries official development assistance (ODA) and total ODA that comes from all donors. To disentangle the net effect of food aid on the other forms of aid from DAC or on the other donor countries aid, we employ the number of natural disaster affected people in other SSA countries as an IV for domestic emergency food aid.

3.4 Results

Table 3.2: The Effect of Food Aid on Civil Conflict Incidence

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Dependent Variable:	Civil conflict incidence			
Panel A: Second-stage estimates				
Emergency food aid	0.0031**	-0.0018	-0.0018	-0.0011
	(0.0014)	(0.0003)	(0.0074)	(0.0071)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
The number of natural disasters affected people in other countries		-0.0016***	-0.0016***	-0.0017***
		0.0003	0.0003	0.0003
Kleibergen-Paap F-statistic		23.32	23.32	25.62
Controls:				
Total damage	Yes	No	No	Yes
Total number of homeless people	Yes	No	No	Yes
Total deaths	Yes	No	No	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	No	Yes	Yes
Instrumental variable	No	Yes	Yes	Yes
Number of countries	30	30	30	30
Observations	630	630	630	630
Pseudo R^2	0.0590	0.0033	0.0033	0.0131

Note: ***Panel A*** shows the OLS and the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.1 Baseline Results

Emergency food aid and civil conflict incidence: Table 3.2 presents the baseline estimates of the effect of emergency food aid on *civil conflict incidence*, where we report the OLS estimates in Column (1) and instrumental variable (IV) estimates in Columns (2)-(4). In Column (2), we control country fixed effects and year fixed effects. In Column (3), we include a country specific time trend. In Column (4), we control for the effect of domestic natural disaster on the incidence of domestic civil conflict. For inference, we report the kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors.

In Panel A, the OLS regression shows that emergency food aid has a positive and statistically significant effect on civil conflict incidence. However, when an instrument for emergency food aid is used, the latter does not have a statistically significant effect on civil conflict incidence. Hence, there is no statistical evidence that emergency food aid from DAC countries (except U.S.) could cause civil conflict incidence in the SSA.

Our instrument for food aid is also strong, which lends credibility to the above second stage estimate. Specifically, the fist stage results of the 2SLS estimation are reported in Columns (2) and (3) of Panel B. Here, we find that emergency food aid is negatively associated with the number of natural disaster affected people in the other SSA countries, and this association is statistically significant at the 1% level. Moreover, the Kleibergen-Paap F (KPF) statistic is larger than 10 in all specifications, suggesting that our IV is not weak.

Emergency food aid and civil war incidence: Table 3.3 presents the estimated coefficients for the effect of emergency food aid on *civil war incidence*. Here, both the OLS and 2SLS estimates show that emergency food aid do not have a statistically significant effect on the incidence of emergency civil war in the SSA. These results are caused by weak IV, as Panel B shows that the instrument (the number of natural disaster affected people in the other countries) is not only statistically significant for emergency food aid (i.e. the endogenous variable), but also has the KP F-statistic that exceeds the rule-of-thumb threshold of 10 (below which, there is evidence of weak IV). Thus, there is again no statistical evidence that food aid from DAC countries affects the incidence civil war in the SSA.

What do these results imply? Firstly, they raise questions about whether food aid does have important effects on conflict, which is what Nunn and Qian (2014) and Chu et al. (2017) have concluded. Secondly, if food aid only has weak effects on conflict at best, then policymakers could continue to employ food aid as tool for helping to fight hunger and suffering in developing countries.

Table 3.3: The Effect of Food Aid on Civil War Incidence

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Dependent Variable (Panel A):	Civil war incidence			
Panel A: Second-stage estimates				
Emergency food aid	0.0011	0.0049	0.0049	0.0040
	(0.0008)	(0.0046)	(0.0046)	(0.0044)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
The number of natural disasters		-0.0016***	-0.0016***	-0.0017***
affected people in other countries		0.0003	0.0003	0.0003
Kleibergen-Paap F-statistic		23.32	23.32	25.62
Controls:				
Total damage	Yes	No	No	Yes
Total number of homeless people	Yes	No	No	Yes
Total deaths	Yes	No	No	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	No	Yes	Yes
Instrumental variable	No	Yes	Yes	Yes
Number of countries	30	30	30	30
Observations	630	630	630	630
Pseudo R^2	0.0466	0.0104	0.0104	0.0415

Note: ***Panel A*** shows the OLS and the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.2 Robustness Checks

Table 3.4: Using the First Lag of Disaster Affected People as an IV

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Dependent Variable (Panel A):	Civil conflict incidence		Civil war incidence	
Panel A: Second-stage estimates				
Emergency food aid	0.0023 (0.0108)	0.0014 (0.0113)	0.0062 (0.0068)	0.0062 (0.0070)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
Lag of the number of natural disasters affected people in other countries	-0.0011*** 0.0003	-0.0011*** 0.0003	-0.0011*** 0.0003	-0.0011*** 0.0003
Kleibergen-Paap F-statistic	10.29	9.69	10.28	9.69
Controls:				
Total damage	No	Yes	No	Yes
Total number of homeless people	No	Yes	No	Yes
Total deaths	No	Yes	No	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes
Instrumental variable	Yes	Yes	Yes	Yes
Number of countries	30	30	30	30
Observations	600	600	600	600
R^2	0.1237	0.1266	0.1237	0.1266

Note: ***Panel A*** shows the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lag of affected people in other countries as IV: In some cases, an increase in emergency food aid demanded by other SSA countries may not immediately reduce the amount of emergency food aid in the home country (due to pledges to give aid and commitment purposes by donors). Therefore, the contemporaneous number of foreign disaster affected people may only be weakly associated with the amount of emergency food aid received.

As a robustness check, we use the previous year (i.e. $t-1$) natural disaster affected people in the other SSA countries as an IV for contemporaneous (period t) emergency food aid and report the new 2SLS estimates in Table 3.4. Just like our baseline estimates, Panel A shows that emergency food aid increases the incidence of civil conflict and civil war in the SSA; but the estimates are statistically insignificant. Therefore, whether or not we use contemporaneous or lagged number of foreign disaster affected people as an instrument does not overturn the statistical insignificance of food aid on civil conflict.

Table 3.5: Controlling Lag of Conflict as an Additional Control Variable

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Dependent Variable (Panel A):	Civil conflict incidence		Civil war incidence	
Panel A: Second-stage estimates				
Emergency food aid	0.0028**	-0.0010	0.0002	0.0024
	(0.0014)	(0.0077)	(0.0008)	(0.0046)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
The number of natural disaster affected people in other countries		-0.0016***		-0.0016***
		0.0003		0.0003
Kleibergen-Paap F-statistic		22.477		21.967
Controls:				
Lag dependent variable	Yes	Yes	Yes	Yes
Total damage	Yes	Yes	Yes	Yes
Total number of homeless people	Yes	Yes	Yes	Yes
Total deaths	Yes	Yes	Yes	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes
Instrumental variable	No	Yes	No	Yes
Number of countries	30	30	30	30
Observations	600	600	600	600
R^2	0.2481	0.1450	0.3332	0.1543

Note: ***Panel A*** shows the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Controlling for lag conflict: Thus far, we have not controlled for the possibility that civil conflict is persistent. Here, we control the fist lag of civil conflict to capture the persistence and dynamics of conflict in the SSA. Table 3.5 presents the OLS and the 2SLS estimates when the first lag of conflict is controlled for. The OLS estimates show that emergency food aid increases civil conflict incidence but not civil war incidence. However, when we address the endogeneity problem (Column (2) and

Column (4)), emergency food aid has no statistically significant effect on both large scale and small scale civil conflict. Therefore, the observed effect of food aid on conflict in the baseline result is not an artifact of omitting the first lag of conflict in the regression equations.

3.4.3 Falsification Tests

The basic identification assumption –that we employ to isolate the effect of food aid on conflict– in our baseline result states that as the number of natural disaster affected people in period t increases in other SSA countries, then the amount of emergency food aid received by the unaffected or less favorite affected countries should shrink in period t as these countries compete for food aid.

In this section, we present a falsification test to examine the validity of the identification strategy. The idea is that if our identification strategy is correct, then the *effect of future* natural disasters in other SSA countries should not affect the amount of contemporaneous (period t) emergency food aid in the SSA. As such, we employ the period $t+1$ and $t+2$ number of natural disaster affected people in the SSA to instrument period t emergency food aid, and we expect the first stage regression estimates on the IV's coefficient to be statistically insignificant.

Table 3.6 reports the estimates for the falsification tests. Columns (1) and (2) present the falsification tests when the number of affected people in $t+1$ affected people is used as instrument of contemporaneous emergency food aid. Columns (3) and (4) report the estimates when the number of affected people in $t+2$ is used as an instrument instead. As the first stage estimates show, the effects of future (i.e. period $t+1$ and $t+2$) natural disaster affected people do not have a statistical significant effect on contemporaneous emergency food aid in the SSA. Moreover, the estimated coefficients are also very small in magnitude. Hence, the falsification test results provide some evidence on the validity of the identification strategy employed for our baseline regression.

Table 3.6: The Effect of Food Aid on Civil Conflict Incidence: Falsification Test

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Dependent Variable (Panel A):	Civil conflict incidence		Civil war incidence	
Panel A: Second-stage estimates				
Emergency food aid	-0.0102	-0.0204	-0.0161	-0.0045
	(0.0253)	(0.0358)	(0.0184)	(0.0189)
Dependent Variable	Emergency Food Aid (t)			
Panel B: First-stage estimates				
The number of natural disasters affected people in other countries, $(t+1)$	0.0005		0.0004	
	0.0003		0.0003	
The number of natural disasters affected people in other countries, $(t+2)$		0.0004		0.0004
		0.0003		0.0003
Kleibergen-Paap F-statistic	2.25	1.336	2.25	1.336
Controls:				
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes
Instrumental variable	Yes	Yes	Yes	Yes
Number of countries	30	30	30	30
Observations	600	600	600	600
R^2	0.1183	0.1182	0.1183	0.1182

Note: ***Panel A*** shows the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. Centered R^2 is reported for the first stage regression of Panel B. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.4 Crowding Out Effects

Table 3.7: Food Aid and Conflict: Crowding Out Food Production and Import

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Dependent Variable (Panel A):	Food import		Cereal production	
Panel A: Second-stage estimates				
Emergency food aid	0.0221*	0.0060	7628.909	-26880.48
	(0.0119)	(0.1043)	(6473.161)	(23287.14)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
The number of natural disaster affected people in other countries		-0.0015***		-0.0015***
		0.0004		0.0003
Kleibergen-Paap F-statistic		13.835		18.115
Controls:				
Total damage	Yes	Yes	Yes	Yes
Total number of homeless people	Yes	Yes	Yes	Yes
Total deaths	Yes	Yes	Yes	Yes
GDP per capita	Yes	Yes	Yes	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes
Instrumental variable	No	Yes	No	Yes
Number of countries	27	25	30	30
Observations	392	390	588	588
R^2	0.0159	0.1450	0.0182	0.1540

Note: ***Panel A*** shows the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Food aid, cereal production and food import: Emergency food aid may affect conflict by influencing domestic cereal production and food import. For example, the quantity of food aid declines in a country if the effect of natural disasters increase in the foreign country. Lower emergency food aid may increase food import or domestic cereal production. As such, the availability of large quantity of food in the country may intern reduce or increase (when food is used to finance military equipments) domestic conflict. In order to check the effect of food aid on food import and food production, we re-estimate Eq. (3.1) using OLS and 2SLS estimation techniques where the dependent variable is replaced by food import and food production.

Table 3.7 presents the estimated results. Except the OLS estimate in Column (1), all the other coefficients are statistically insignificant. The statistically significant estimate in Column (1) may be because of endogeneity problem (as a result of reverse causality, omitted variable or measurement errors). When we address the endogeneity problem using an instrumental variable (see Column (2)), the effect of food aid on food import becomes statistically insignificant. The Kleibergen-Paap F-statistic is also greater than 10 for the two 2SLS regression models suggesting that our instrument is not weak. Therefore, this implies that emergency aid may not crowd-out (crowd-in) domestic cereal production and food import in the SSA.

Food aid and other forms of aid: Food aid may also affect civil conflict by crowding-out other forms of aid such as official development assistance (ODA). Several empirical studies have shown that foreign aid may increase (Grossman, 1992) or decrease (De Ree and Nillesen, 2009) the risk of civil conflict in the aid recipient countries. As such, foreign aid may increase or decrease the incidence of conflict if it is crowded out by food aid. We test the effect of food aid on ODA from the 29 DAC countries and U.S. as well as on net ODA from all donor countries.

The estimated 2SLS results are reported in Table 3.8. As the estimated coefficients in Panel A illustrate, emergency food aid does not have any statistically significant effect on ODA from different donor countries. This suggests that food aid does not have a crowding-out effect on other forms of aid. As such, our baseline results (in Table 3.2 and 3.3) are not driven by factors other than emergency food aid from the 29 DAC countries.

3.4.5 Additional Robustness Checks

Alternative sample: Up to now our analysis focuses on all the 30 sample SSA countries. However, observing Figure 3.3, we notice that some outlier countries might have derived our baseline results. For example, the relationship between emergency food aid and foreign disaster affected people looks positive for Sudan which contradicts our identification assumption between the two variables. Hence,

Table 3.8: Food Aid and Conflict: Crowding Out Other Forms of Foreign Aid

	(1) 2SLS	(2) 2SLS	(3) 2SLS
Dependent Variable (Panel A):	U.S. ODA	Other DAC ODA	Net ODA
Panel A: Second-stage estimates			
Emergency food aid	3402437	-4648318	403444.4
	(2721117)	(11600000)	(15800000)
Dependent Variable		Emergency Food Aid	
Panel B: First-stage estimates			
The number of natural disaster affected people in other countries	-0.0015***	-0.0015***	-0.0015***
	0.0003	0.0003	0.0003
Kleibergen-Paap F-statistic	17.694	17.694	18.206
Controls:			
Total damage	Yes	Yes	Yes
Total number of homeless people	Yes	Yes	Yes
Total deaths	Yes	Yes	Yes
GDP per capita	Yes	Yes	Yes
Country Fixed effects	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes
Country specific time trend	Yes	Yes	Yes
Number of countries	30	30	30
Observations	573	573	590
R^2	0.1525	0.1525	0.1540

Note: ***Panel A*** shows the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

we check the sensitivity of the baseline results by excluding Sudanese data from the analysis. Table 3.9 presents the estimated results. Observing our preferred two-stage estimates in Column (2) and Column (4) show that emergency food aid does not have a statistically significant effect on both civil conflict and civil war incidence in the SSA. Hence, there is no evidence that our baseline results (Table 3.2 and 3.3) are driven by outliers in the dataset.

Table 3.9: Using Alternative Sample Countries

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Dependent Variable (Panel A):	Civil conflict incidence		Civil war incidence	
Panel A: Second-stage estimates				
Emergency food aid	0.0019 (0.0015)	-0.00033 (0.0068)	0.0024*** (0.0009)	0.0032 (0.0040)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
The number of natural disaster affected people in other countries		-0.0018*** 0.0003		-0.00176*** 0.0003
Kleibergen-Paap F-statistic		29.261		29.261
Controls:				
Total damage	Yes	Yes	Yes	Yes
Total number of homeless people	Yes	Yes	Yes	Yes
Total deaths	Yes	Yes	Yes	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes
Instrumental variable	No	Yes	No	Yes
Number of countries	29	29	29	29
Observations	609	609	609	609
R^2	0.0431	0.1527	0.0512	0.1527

Note: ***Panel A*** shows the second stage estimates of the 2SLS estimation. ***Panel B*** shows the first stage estimates of the 2SLS estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.6 Spatial Conflict Spillover in sub-Saharan Africa

So far, we do not consider civil conflict spillover from one country to its neighbor as the sub-Saharan African countries are assumed to be interdependent of each other in terms of spreading conflict. However, several anecdotal accounts show that civil conflict has a tendency to spillover from one country to the other (Bosker and de Ree, 2014). The main channels for the cross-country spillover of conflict are refuge inflows, high degree of ethnic separation (which tends to increase the creation of alliances among armed groups who are located in different countries), poor institutional environment and the presence of abundance natural resource stock (Carmignani and Kler, 2016a). As these channels are pervasive in the SSA, conflict spillover is likely to be more frequent and persistent in the SSA than elsewhere (Carmignani and Kler, 2016a,b; Bosker and de Ree, 2014). Despite these explanations, several SSA countries also experience higher risk of civil conflict independent of what happens in their neighbor (see e.g. Gleditsch, 2007) making the strength of civil conflict spillover ambiguous.

To consider the spatial dimension of war and to test the sensitivity of our baseline results for spatial conflict contagion, we include a spatially lagged dependent variable that captures the spatial spillover of conflict among SSA countries on the right hand side of Eq. (3.1) and (3.2). Hence, following Carmignani and Kler (2016b), our spatial-lag second stage regression equation is specified as:

$$Conflict_{it} = \rho \mathbf{W}_y Conflict_{it} + \beta(FoodAid)_{it} + X_{it}\Gamma + \varphi_t + \psi_i + \mu_{it} \tag{3.3}$$

Where $Conflict_{it}$ is an indicator variable which equals to 1 in country i and period t if 25-1000 battle related deaths are recorded for civil conflict incidence or if more than 1000 battle related deaths are recorded for civil war incidence; and 0 otherwise. ρ denotes the coefficient of the spatial-lag variable, $\mathbf{W}_y$ represents the spatial weighting matrix for country i and lag year y and hence describe the spatial dependent structure. Therefore, $\mathbf{W}_y Conflict_{it}$ represents the year y spatially lagged conflict spillover on country i and period t, where $i \neq j$. We follow Kondo (2017) to construct spatial weighting matrix and to generate the spatial lagged variables. We generate the first order and the second order spatially lagged conflict measures of civil conflict incidence and civil war incidence. Appendix (B) presents the Moran scatter plots that visualize the relationship between $Conflict_{it}$ and $\mathbf{W}_y Conflict_{it}$. The plots show a strong positive correlation between $Conflict_{it}$ and $\mathbf{W}_2 Conflict_{it}$ but the relationship between $Conflict_{it}$ and $\mathbf{W}_1 Conflict_{it}$ is very weak.

Table 3.10: Food Aid and Conflict (War) Incidence: with Spatial Interdependence

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Dependent Variable (Panel A):	Conflict	War	Conflict	War
Panel A: Second-stage estimates				
Emergency food aid	-0.0011	0.0041	-0.0061	0.0061
	(0.0071)	(0.0043)	(0.0069)	(0.0039)
Spatial lag of incidence ($t-1$)	0.0036	0.0422		
	(0.0459)	(0.0483)		
Spatial lag of incidence ($t-2$)			0.3881***	0.5235***
			(0.0474)	(0.0449)
Dependent Variable	Emergency Food Aid			
Panel B: First-stage estimates				
The number of natural disasters affected people in other countries	-0.0017***	-0.0017***	-0.0017***	-0.0017***
	0.0003	0.0003	0.0003	0.0003
Kleibergen-Paap F-statistic	26.069	25.617	24.679	25.549
Controls:				
Other controls	Yes	Yes	Yes	Yes
Country Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Country time trend	Yes	Yes	Yes	Yes
Number of countries	30	30	30	30
Observations	630	630	630	630
R^2	0.1475	0.1470	0.1483	0.1467

Note: ***Panel A*** and ***Panel B*** show the second and the first stage estimates of the 2SLS estimation. *Other controls* include total deaths, total homeless and total damage in the country. Kernel-based heteroskedastic and autocorrelation consistent (HAC) standard errors are used for the 2SLS analysis. Centered R^2 is reported for the first stage regression of Panel B. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10 presents the estimated results. In Columns (1) and (3), we control the first and the second spatial lags of civil conflict incidence, respectively. Whereas in Columns (2) and (4), we control the first and the second spatial lags of civil war incidence, respectively. We also control all the potential covariates that may affect the incidence of conflict. As Columns (1) and (2) of Panel A show the first spatial lag conflict measures do not have a statistically significant effect on the risk of contemporaneous civil conflict (civil war) incidence. On the contrary, Columns (3) and (4) demonstrates that the second spatial lags of conflict has a positive and statistically significant effect on the incidence of contemporaneous conflict suggesting conflicts in the neighboring country spillovers after two years. However, despite the large positive and statistically significant effect of the spatial second lag conflict measures; the sign, the magnitude and the statistical significance of the emergency food aid coefficients are close to the baseline estimates. Hence, the estimates that we find in the baseline tables (i.e. Table 3.2 and 3.3) are not an artifact of omitting the spatial interdependence of conflict among the SSA countries.

3.5 Conclusion

Emergency food aid is provided to alleviative hunger and suffering in poor countries. However, the effectiveness of food is questioned in recent years in achieving its objective. Food aid is also accused to increase conflict incidence when provided to conflict prone developing countries. This paper investigates the causal effect of emergency food aid on civil conflict in sub-Saharan Africa. We find evidence that food aid from DAC countries (except U.S. food aid) does not exacerbate civil conflict in the SSA. The findings suggest that humanitarian aid is still a useful international policy tool to alleviate hunger and suffering in disaster affected developing countries.

References

Bartik, T. J. (1991). Who benefits from state and local economic development policies?

Bazzi, S. and M. A. Clemens (2013). Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth. *American Economic Journal: Macroeconomics 5*(2), 152–86.

Bosker, M. and J. de Ree (2014). Ethnicity and the spread of civil war. *Journal of Development Economics 108*, 206–221.

Bourguignon, F. and M. Sundberg (2007). Aid effectiveness–opening the black box. *American Economic Review 97*(2), 316–321.

Buhaug, H., S. Gates, and P. Lujala (2009). Geography, rebel capability, and the duration of civil conflict. *Journal of Conflict Resolution 53*(4), 544–569.

Carmignani, F. and P. Kler (2016a). The geographical spillover of armed conflict in sub-Saharan Africa. *Economic Systems 40*(1), 109–119.

Carmignani, F. and P. Kler (2016b). Surrounded by wars: Quantifying the role of spatial conflict spillovers. *Economic Analysis and Policy 49*, 7–16.

Christian, P. J. and C. B. Barrett (2017). Revisiting the effect of food aid on conflict: A methodological caution. *World Bank Policy Research Working Paper* (No. 8171).

Chu, C.-Y., D. J. Henderson, and L. Wang (2017). The robust relationship between us food aid and civil conflict. *Journal of Applied Econometrics 32*(5), 1027–1032.

Crost, B., J. Felter, and P. Johnston (2014). Aid under fire: Development projects and civil conflict. *American Economic Review 104*(6), 1833–56.

De Ree, J. and E. Nillesen (2009). Aiding violence or peace? the impact of foreign aid on the risk of civil conflict in sub-Saharan Africa. *Journal of Development Economics 88*(2), 301–313.

Galiani, S., S. Knack, L. C. Xu, and B. Zou (2017). The effect of aid on growth: Evidence from a quasi-experiment. *Journal of Economic Growth 22*(1), 1–33.

Gleditsch, K. S. (2007). Transnational dimensions of civil war. *Journal of Peace Research 44*(3), 293–309.

Grossman, H. I. (1992). Foreign aid and insurrection. *Defence and Peace Economics 3*(4), 275–288.

Kondo, K. (2017). Spgen: Stata module to generate spatially lagged variables.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy 112*(4), 725–753.

Nunn, N. and N. Qian (2014). US food aid and civil conflict. *American Economic Review 104*(6), 1630–66.

Pettersson, T. and P. Wallensteen (2015). Armed conflicts, 1946–2014. *Journal of Peace Research 52*(4), 536–550.

USAID (2014). (Re)Assessing the relationship between food aid and armed conflict. Technical report.

Werker, E., F. Z. Ahmed, and C. Cohen (2009). How is foreign aid spent? evidence from a natural experiment. *American Economic Journal: Macroeconomics 1*(2), 225–44.

Appendix A: List of Donor and Recipient Countries

Table A1: The List of Development Assistant Committee (DAC) Donor Countries

Australia	Austria	Belgium	Canada
Czech Republic	Denmark	Finland	France
Germany	Greece	Hungary	Iceland
Ireland	Italy	Japan	Korea
Luxembourg	Netherlands	New Zealand	Norway
Poland	Portugal	Slovak Republic	Slovenia
Spain	Sweden	Switzerland	United Kingdom

Note: As noted, we exclude U.S. in our analysis. Our study covers the period between 1995 and 2015.

Table A2: The List of Aid Recipient Sample sub-Saharan African Countries

Algeria	Angola	Burundi	Cameroon
Central Africa R.	Chad	Congo	D.R. Congo
Djibouti	Egypt	Eritrea	Ethiopia
Guinea	Guinea-Bissau	Ivory Coast	Kenya
Lesotho	Liberia	Libya	Mali
Mauritania	Mozambique	Niger	Nigeria
Rwanda	Senegal	Sierra Leone	Somalia
Sudan	Uganda		

Note: The sample aid recipient countries of the study are chosen based on the availability of data.

Appendix B: Moran Scatter Plot of Conflict Incidence

Figure 3.5: Moran's Scatter Plot - Civil Conflict Incidence

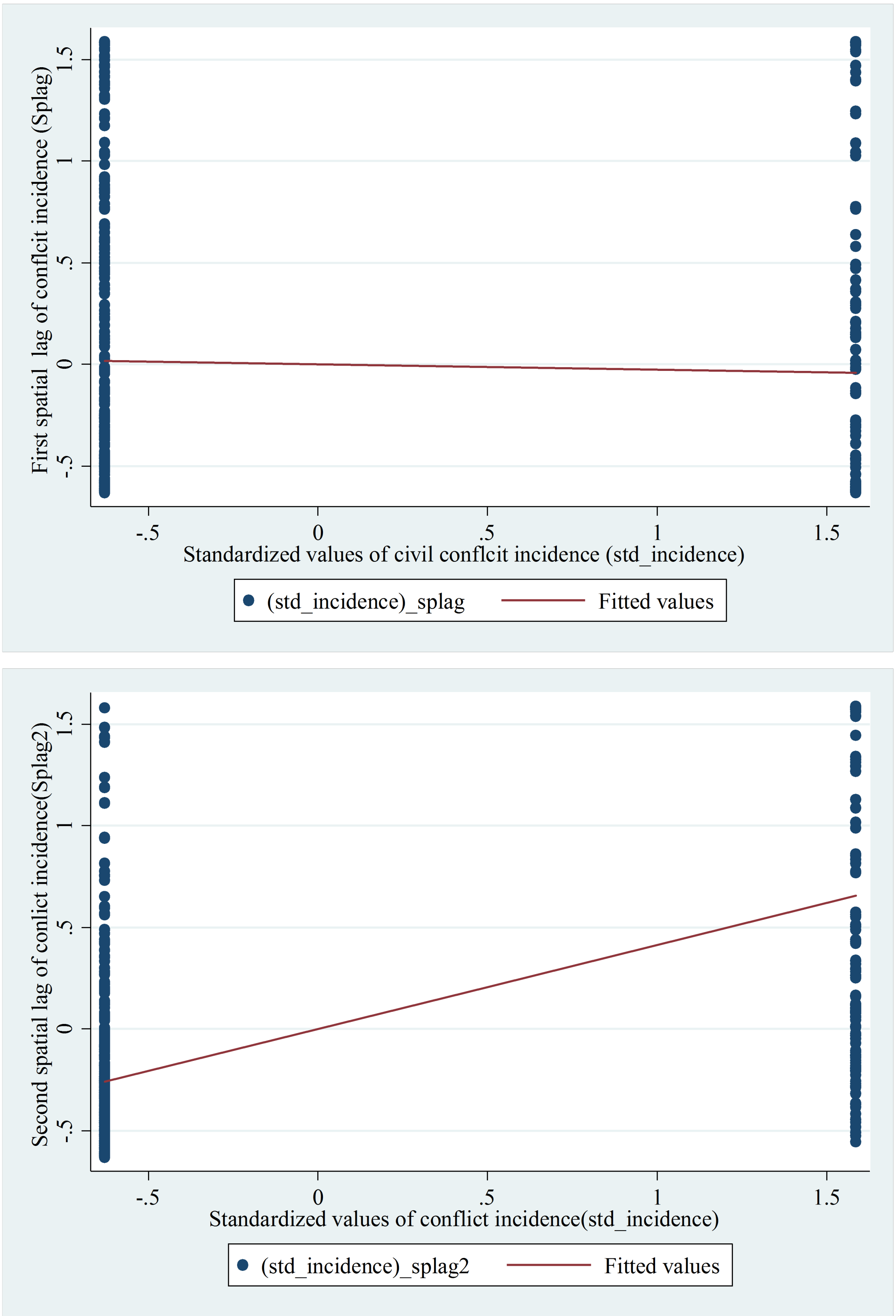
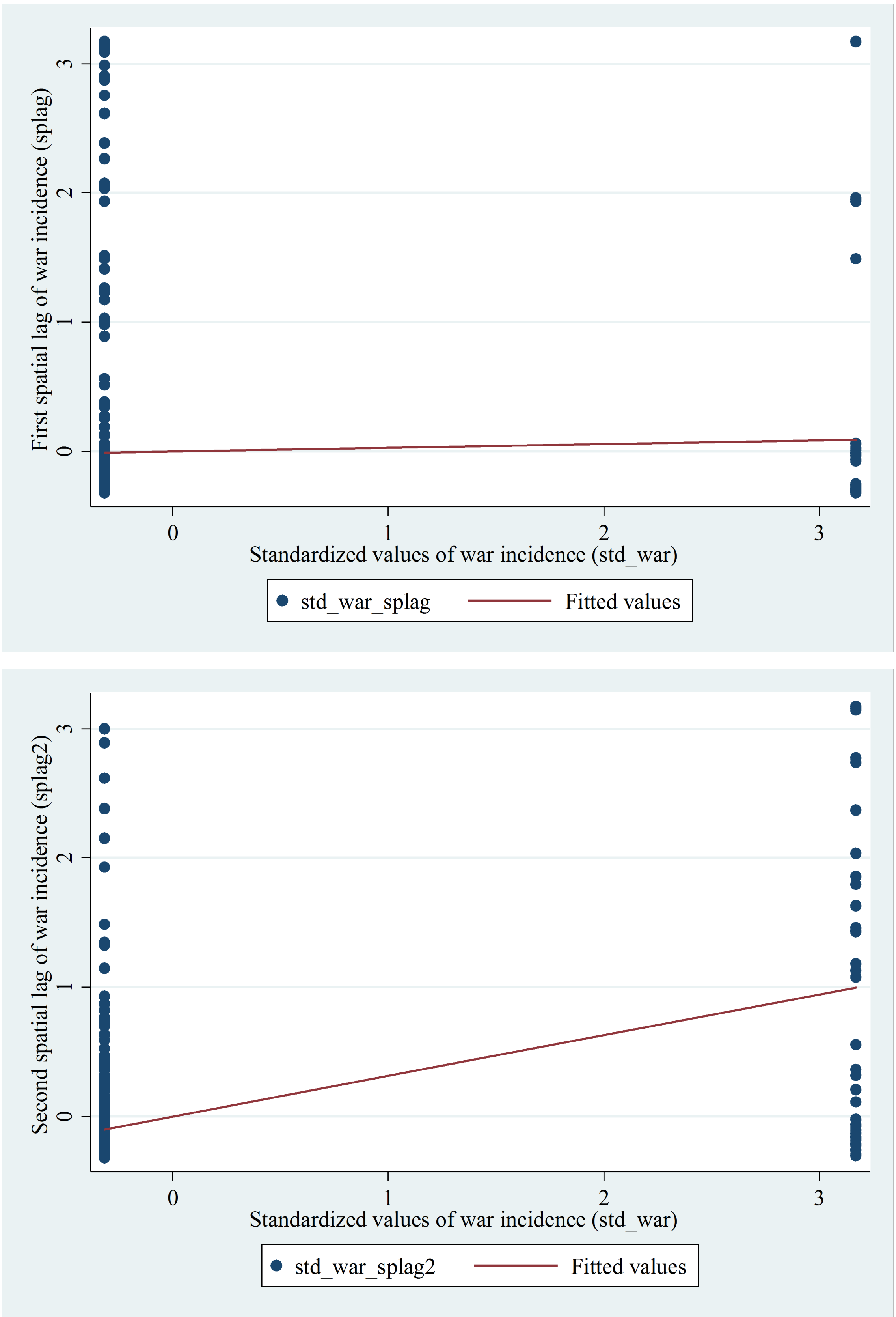


Figure 3.6: Moran's Scatter Plot - civil War Incidence



Chapter 4

Is Inflation Targeting or the Fixed Exchange Rate More Effective for Attracting FDI into Developing Countries?

Dessie Tarko Ambaw[a] Nicholas Sim[a]

[a] *School of Economics, The University of Adelaide*

This paper is published in *Applied Economics Letters*: June 2017

https://doi.org/10.1080/13504851.2017.1340563

Statement of Authorship

Title of Paper	Is Inflation Targeting or the Fixed Exchange Rate More Effective for Attracting FDI into Developing Countries?
Publication Status	☑ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	The paper is published at the Applied Economic Letters in 2017 as Ambaw, D. T., & Nicholas Sim. (2017). "Is inflation targeting or the fixed exchange rate more effective for attracting FDI into developing countries?". Applied Economics Letters.

Principal Author

Name of Principal Author (Candidate)	Dessie Tarko Ambaw		
Contribution to the Paper	Contributed to planning the article and the methodology, conducted the literature review, collected the data, analysed and interpreted the results, wrote part of the manuscript and acted as the corresponding author.		
Overall percentage (%)	85%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper		
Signature		Date	06/09/2018

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Nicholas Sim		
Contribution to the Paper	Contributed to the planning of the article, supervised the development of the work, helped in the interpretation of the results and wrote part of the manuscript.		
Signature		Date	06/09/2018

Abstract

This paper investigates which monetary policy regime –inflation targeting or the fixed exchange rate– is more effective for attracting FDI inflows into developing countries. Using propensity score matching and the difference-in-differences estimator, we find no evidence that adopting an inflation targeting regime would be more effective than adopting a fixed exchange rate, and vice-versa, in encouraging FDI inflows.

Key Words: Inflation Targeting, Fixed Exchange Rate, FDI

JEL Codes: C21, E52, E58, F21, F31

4.1 Introduction

There is some concern that the uncertainty of economic policy – in particular, of monetary policy – may lead to less inward FDI into developing countries (Rodrik (1991), Pindyck (1991), and Wang et al. (2014)).[1] To reduce this uncertainty, many countries have turned to targeting inflation or adopting a fixed exchange rate as their monetary policy regime. Although there is evidence that both are effective for encouraging inward FDI,[2] whether or not one policy is more effective than the other is unclear. Having some guidance on this issue is especially important from the perspective of a developing country seeking to commit itself to one policy regime over the other.

This paper contributes to the literature by investigating which policy regime – inflation targeting or the fixed exchange rate – is more effective for attracting FDI inflows into developing countries. The main estimation issue here arises from the possibility that the policy regimes adopted by countries could be self-selected. To address this issue, we implement propensity score matching and the difference-in-differences estimator. We find no evidence that inflation targeting or the fixed exchange rate is more effective than the other in encouraging FDI inflows.

4.2 Data

This study uses a panel data on 46 developing countries (listed in Table A1 of the Appendix) that adopt either inflation targeting or a fixed exchange rate between 1990 to 2006. Table 4.1 provides the summary statistics of the variables that are used in this study.

[1] Developing countries here mostly refer to middle income counties but not lower income or least developing countries.

[2] See, for example, Abbott et al. (2012) for fixed exchange rates and Tapsoba (2012) for inflation targeting.

Table 4.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Inflation targeting	0.139	0.346	0	1	850
Exchange rate targeting	0.567	0.496	0	1	818
FDI (% of GDP)	3.379	3.943	-2.757	36.072	768
Trade openness	83.409	59.05	13.753	430.358	808
Broad money growth	48.091	279.34	-45.473	6384.916	784
Real GDP per-capita	5429.592	5315.048	464.871	31514.371	796
Country size	0.402	0.664	0	5.22	797
CBG turnover rate	0.192	0.394	0	1	814
Fiscal balance	-0.973	4.119	-18.402	20.338	443
Financial openness	0.483	0.351	0	1	774
School enrollment	77.192	19.029	20.381	109.177	681
Taxes (% of revenue)	21.624	12.236	1.598	64.302	471
Political constraint	0.334	0.198	0	0.688	825
Government expenditure	14.58	5.046	2.976	29.996	794
Mobile subscriptions	18.476	28.6	0	145.677	850
Telephone subscriptions	18.485	12.983	0.588	57.463	850
Inflation rate	62.09	386.745	-4.023	7481.664	744

4.3 Methodology

Without loss of generality, we consider inflation targeting as the treatment. To estimate the treatment effect (of inflation targeting) on FDI, we need to address the issue of self-selection by countries into the inflation targeting or fixed exchange rate regime. If this self-selection can be modeled as the dependence of the regime choice on certain observable covariates and time invariant unobservable factors that matter for FDI, we may address this issue by implementing propensity score matching (PSM) and the difference-in-differences (DiD) estimator.

The PSM approach addresses the issue of self-selection that arises from the correlation between the policy choice and the country's observed characteristics. The validity of this approach depends on satisfying the conditional independence assumption (CIA), which states that conditioning on certain observables as summarized by the propensity score, a country's unobservable characteristics are orthogonal to its policy choice. To implement the PSM approach, we estimate the probability (i.e. the propensity score) that a country adopts a certain policy regime conditional on a set of observables:

$$P(Y_{it} = 1|\mathbf{Z}_{it}) = \Phi(\boldsymbol{\gamma}'\mathbf{Z}_{it}) \tag{4.1}$$

where Y_{it} is an indicator variable that is equal to 1 if country i adopts an inflation targeting regime in period t and 0 if it adopts a fixed exchange rate regime, $\mathbf{Z}_{it}$ is a set of observables that may affect country i's probability of choosing to target inflation over a fixed exchange rate, and Φ is the standard normal *cdf*.

Next, we use the estimated propensity scores to match countries that adopt inflation targeting (the treated group) with countries that adopt a fixed exchange rate (the comparison group), so that if the CIA assumption holds, the treatment (i.e. inflation targeting) will be as good as randomly assigned. In this paper, we apply three different techniques – nearest-neighbor, kernel, and stratification – to match the two sets of countries. Following which, we calculate the average treatment effect of inflation targeting as the difference in the means of FDI inflows between the inflation targeting and fixed exchange rate countries.

Besides the PSM approach, we employ the DiD estimator to estimate if on average, the adoption of inflation targeting would generate larger FDI inflows than if a fixed exchange rate was adopted. This is achieved by estimating

$$FDI_{it} = \beta \mathit{Inflation\_Targeting}_{it} + \boldsymbol{\delta}'\mathbf{X}_{it} + \mu_i + \mu_t + \varepsilon_{it} \tag{4.2}$$

where FDI_{it} is the net FDI of country i in year t as a percentage of GDP (used throughout our empirical analysis), $\mathbf{X}_{it}$ is a vector containing the set of FDI determinants, μ_i and μ_t represent the country and year fixed effects respectively. The treatment effect of inflation targeting is captured by the coefficient (β) on $\mathit{Inflation\_Targeting}_{it}$, where $\mathit{Inflation\_Targeting}_{it}$ is equal to 1 if country i adopts inflation targeting in time t and 0 if otherwise (i.e. adopts a fixed exchange rate).

We follow the literature in choosing the benchmark covariates $\mathbf{Z}_{it}$ and $\mathbf{X}_{it}$ for the PSM and DiD approaches respectively, although we have found that our main conclusion is unaffected by using the same set of covariates for both approaches as well.[3] All the variables used here, their definitions, and source are listed in Table A2 of the Appendix.

Table 4.2: Probit Estimates of the Likelihood of Adopting Inflation Targeting

Covariates	(1) Benchmark Model	(2) (+) CBG Turnover Rate	(3) (+) Fiscal Balance	(4) (+) Financial Openness	(5) (−) Hyper-Inflation Episodes
Inflation Lag	-6.289^{***}	-6.308^{***}	-14.511^{***}	-13.556^{***}	-13.556^{***}
	(2.177)	(2.188)	(4.125)	(4.064)	(4.064)
Trade Openness	-0.016^{***}	-0.016^{***}	-0.007^{**}	-0.006^{*}	-0.006^{*}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Broad Money Growth	-0.027^{***}	-0.027^{***}	-0.024^{**}	-0.024^{**}	-0.024^{**}
	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)
Real GDP Per-Capita	0.000^{***}	0.000^{***}	0.000	0.000^{*}	0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Country Size	0.201^{*}	0.197^{*}	1.373^{***}	1.296^{***}	1.296^{***}
	(0.106)	(0.106)	(0.277)	(0.284)	(0.284)
CBG Turnover Rate		−0.132	−0.215	−0.244	−0.244
		(0.251)	(0.337)	(0.340)	(0.340)
Fiscal Balance			-0.127^{***}	-0.139^{***}	-0.139^{***}
			(0.049)	(0.050)	(0.050)
Financial Openness				−0.499	−0.499
				(0.453)	(0.453)
Constant	0.092	0.133	−0.372	−0.247	−0.247
	(0.309)	(0.314)	(0.451)	(0.457)	(0.457)
Observations	407	397	247	244	241
Pseudo R^2	0.310	0.307	0.440	0.442	0.439

Standard errors in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Results

4.4.1 The Propensity Scores Matching Estimates

Column (1) of Table 4.2 reports the effect that various observable characteristics have on a country's likelihood of choosing to target inflation (as opposed to a fixed

[3]See, for example, Lin and Ye (2012) and Tapsoba (2012) for a discussion on the covariates choice for the two approaches. We have also tried using the same set of covariates for $\mathbf{Z}_{it}$ and $\mathbf{X}_{it}$ for both PSM and DiD approaches, e.g. all the covariates found in Column (4) of Table 1 and Column (4) of Table 3, and found that our main conclusion about the effectiveness of inflation targeting versus adopting a fixed exchange rate for attracting FDI remains the same.

exchange rate).[4] We find that the probability of adopting inflation targeting reduces with inflation, trade openness, and broad money growth, but increases with real GDP per-capita and country size.

Table 4.3 reports the matching estimates of the treatment effect of inflation targeting on FDI. For the benchmark model, this effect is statistically insignificant regardless of the matching techniques used. As a robustness check, we vary the set of covariates used in constructing the propensity scores by adding to the benchmark covariates, CBG (Central Bank Governor) turnover rate, fiscal balance and financial openness in a successive manner. Following which, we omit hyperinflation episodes and find that in all instances, the treatment effect of inflation targeting (over adopting a fixed exchange rate) remains statistically insignificant for FDI.

Table 4.3: Matching Estimates of the Treatment Effect of Inflation Targeting on FDI

	Matching Methods		
	Nearest Neighbor Matching	Kernel Matching	Stratification Matching
Benchmark Model	−0.996	0.107	0.203
	(0.817)	(0.456)	(0.526)
(+) CBG Turnover rate	−0.138	0.140	0.114
	(0.787)	(0.464)	(0.499)
(+) Fiscal Balance	0.331	0.458	0.768
	(0.919)	(0.793)	(0.725)
(+) Financial Openness	−0.333	0.622	0.470
	(1.108)	(0.754)	(0.753)
Exclude Hyperinflation Episodes	−0.333	0.622	0.470
	(1.076)	(0.701)	(0.775)

Bootstrap standard errors are in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4.2 The Difference-in-Differences Estimates

Column (1) of Table 4.4 reports the benchmark DiD result and finds that the coefficient on *Inflation_Targeting* is statistically insignificant. Hence, once again, there is no evidence that inflation targeting would outperform the fixed exchange rate in attracting FDI. In addition, as Columns (2)-(4) show, the statistical insignificance of

[4] We have checked that covariates are balanced across treatment and comparison groups.

inflation targeting is not sensitive to varying the set of control variables, even if these control variables matter for FDI. Therefore, the problem of omitted variable bias, even if it exists, is unlikely to be so severe that it overturns our main finding – i.e. inflation targeting is not more effective than fixing the exchange rate for encouraging FDI inflows.

Table 4.4: Difference-in-Differences Estimates of the Treatment Effect of Inflation Targeting on FDI

	(1)	(2)	(3)	(4)
Dependent Variable:	*Net FDI (% of GDP)*			
Inflation_Targeting	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Trade Openness	0.036***	0.035***	0.032***	0.031***
	(0.011)	(0.010)	(0.011)	(0.011)
Per-Capita GDP Growth	0.022	0.019	0.035	0.136l
	(0.062)	(0.059)	(0.069)	(0.086)
School Enrollment	0.010	0.009	0.023	0.017
	(0.013)	(0.014)	(0.017)	(0.017)
Taxes	-0.049**	-0.049**	-0.057***	-0.050**
	(0.020)	(0.021)	(0.022)	(0.024)
Political Constraint	-3.962***	-4.079***	-3.771***	-2.806**
	(1.405)	(1.239)	(1.280)	(1.305)
Government Expenditure	0.064	0.062	0.055	0.068
	(0.063)	(0.068)	(0.066)	(0.066)
Financial Openness	2.814***	2.747***	2.719***	2.246***
	(0.742)	(0.741)	(0.781)	(0.823)
Mobile Subscriptions		0.004	0.012	0.023
		(0.017)	(0.019)	(0.019)
Telephone Subscriptions			-0.036	-0.044
			(0.031)	(0.031)
Inflation Lag				0.885
				(2.087)
Constant	2.993	2.975	2.289	0.957
	(1.935)	(1.957)	(2.054)	(2.072)
N	226	226	226	209
R^2	0.409	0.409	0.414	0.426

Bootstrap standard errors are in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Conclusion

Although there is evidence that countries can encourage FDI inflows by targeting inflation or adopting a fixed exchange rate, it is unknown if one policy is more effective than the other. We offer some clarification on this issue by showing that as long as one of these policies is pursued, there is no perceivable advantage in adopting inflation targeting over a fixed exchange rate (and vice-versa) for attracting FDI.

References

Abbott, A., D. O. Cushman, and G. De Vita (2012). Exchange rate regimes and foreign direct investment flows to developing countries. *Review of International Economics 20*(1), 95–107.

Lin, S. and H. Ye (2012). What to target? inflation or exchange rate. *Southern Economic Journal 78*(4), 1202–1221.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. *Journal of Economic Literature Vol. XXIX*, 1110–1148.

Rodrik, D. (1991). Policy uncertainty and private investment in developing countries. *Journal of Development Economics 36*(2), 229–242.

Tapsoba, R. (2012). Does inflation targeting matter for attracting foreign direct investment in to developing countries? Technical Report No. 201203, "Unpublished Paper".

Wang, Y., C. R. Chen, and Y. S. Huang (2014). Economic policy uncertainty and corporate investment: Evidence from China. *Pacific-Basin Finance Journal 26*, 227–243.

Appendix

Table A1: List of Countries

Inflation Targeting Countries				
Brazil	Chile	Colombia	Czech Republic	Hungary
Israel	Korea	Mexico	Peru	Philippines
Poland	South Africa	Thailand		
Fixed Exchange Rate Countries				
Algeria	Argentina	Belarus	Bulgaria	Cape Verde
China	Costa Rica	Croatia	Dominican Republic	Egypt
Estonia	Georgia	Guatemala	Hong Kong	Indonesia
Iran	Jamaica	Jordan	Kazakhstan	Latvia
Lebanon	Lithuania	Mauritius	Morocco	Paraguay
Russia	Slovak	Slovenia	Trinidad & Tobago	Tunisia
Ukraine	Uruguay	Venezuela		

Note: Countries classified under *Fixed Exchange Rate Countries* adopted a fixed exchange rate throughout the sample period (1990 to 2006). Countries under *Inflation Targeting Countries* adopted the inflation targeting regime for one year or more during the sample period.

Table A2: Variable Definitions and Their Sources

Variable	**Definition**	**Source**
Broad Money Growth	Annual broad money growth	WDI
CBG Turnover Rate	Central bank governor turnover rate	Dreher et al. (2008)
Country Size	GDP as a percentage of world GDP	WDI
FDI	Net foreign direct (% of GDP) investment flows	WDI
Financial Openness	An index of financial openness	Chinn and Ito (2007)
Fiscal Balance	Cash surplus/ deficit (% of GDP)	WDI
Government Expenditure	Government expenditure (% of GDP)	WDI
Inflation Lag	The first order lag of ln(1+CPI inflation/100)	WDI
Inflation Targeting	An inflation targeting dummy	Goncalves and Salles (2008)
Mobile Subscriptions	Mobile cellular subscriptions (per 100 people)	WDI
Per-capita GDP Growth	Annual growth rate of GDP per-capita	WDI
Political Constraint	Index measuring political constraints	POLCON Database
School Enrollment	Gross secondary school enrollment rate	WDI
Taxes	Taxes on income, profits and capital (% of revenue)	WDI
Telephone Subscriptions	Fixed telephone subscriptions (per 100 people)	WDI
Trade Openness	Ratio of exports and imports to GDP	WDI

Chapter 5

Landlockedness, Trade Cost and Trade: Evidence from a Natural Experiment in Ethiopia

Dessie Tarko Ambaw[a] Habtamu Tesfaye Edjigu[a]

Nicholas Sim[a,b]

[a]*School of Economics, The University of Adelaide*

[b]*School of Business, The Singapore University of Social Sciences*

Statement of Authorship

Title of Paper	Landlockedness, Trade Cost and Trade: Evidence from a Natural Experiment in Ethiopia
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	The paper is written in publication style for submission to a journal.

Principal Author

Name of Principal Author (Candidate)	Dessie Tarko Ambaw		
Contribution to the Paper	Contributed to planning the article and the methodology, conducted the literature review, collected the data, analysed and interpreted the results, wrote part of the manuscript and acted as the corresponding author.		
Overall percentage (%)	40%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the co-author of this paper.		
Signature		Date	06/09/2018

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Nicholas Sim		
Contribution to the Paper	Contributed to the planning of the article, supervised the development of the work, helped in the interpretation of the results and wrote part of the manuscript.		
Signature		Date	06/09/2018

Name of Co-Author	Habtamu Tesfaye Edjigu		
Contribution to the Paper	Contributed to the planning of the article and the methodology, conducted the literature review, collected the data, analysed and interpreted the results, wrote part of the manuscript.		
Signature		Date	06/09/2018

Abstract

It is argued that landlocked countries are usually less developed due to landlockedness being a significant barrier to trade. Empirically, however, there is little evidence on how large the causal effect of landlockedness is, as exogenous variations in landlockedness useful for addressing this question are rare. In this paper, we exploit a novel natural experiment when Ethiopia's became a *de facto* landlocked country following a conflict with Eritrea in 1998. Because landlockedness primarily affects land and sea freight than air freight, this "closing in" of Ethiopia should affect the trade of bulky, low-valued goods more strongly than the trade of light, high-valued goods. To estimate the effect of landlockedness, we employ two approaches: the triple difference-in-differences approach and the synthetic control approach. The triple difference-in-differences approach enables us to use a span of fixed effects to identify the "treatment" effect of landlockedness on trade. The synthetic control approach provides us with a data-driven method to obtain a control group that mirrors Ethiopia's pre-intervention trend as closely as possible. Our empirical results reveal that landlockedness has a large negative impact on Ethiopia's exports and imports: on average, being landlocked reduces Ethiopia's ocean-borne exports and imports by about 43-80% and 67-71%, respectively. We also find that the landlockedness shock has a persistent effect on trade, suggesting that the negative influence of landlockedness is not easily overcome.

Key Words: Landlockedness, Trade Cost, Ethiopia, Triple-difference Approach

JEL Codes: C21, F14, F15, O10, P33

5.1 Introduction

It is well-known that landlocked countries tend to be less developed than their coastal neighbors. One explanation is that landlockedness is a significant barrier to trade, which stifles the development of countries with landlocked geography (Raballand, 2003; Faye et al., 2004; Arvis et al., 2010). For example, among developing countries, landlocked developing countries have only a third of the import share of coastal developing countries (World Bank, 1998), and they export less than half of the per-capita volume of their coastal counterparts (Faye et al., 2004). Consequently, they do not trade as much, landlocked developing countries usually have lower levels of socio-economic development as well. Currently, about half the population in these countries live on less than US$2 per day and about 1 in 10 newborns are not expected to live past the age of five.

Given the poverty levels faced by many landlocked developing countries, economists have sought to understand how serious and persistent the problem of landlockedness might be. Unfortunately, this issue is also an extremely difficult one to shed light on. Although landlocked developing countries tend to be poorer, it is unclear if this is due to landlockedness itself, other geographical attributes, unobserved institutions that are somehow correlated with landlocked geography, or other factors. Currently, research on the effects of landlockedness are mostly carried by estimating the coefficient on the landlocked dummy in cross-country regressions with cross-sectional data (e.g. Limao and Venables, 2001; Raballand, 2003; Coulibaly and Fontagné, 2006; World Bank, 2014). This estimated coefficient, as researchers have acknowledged, may not reflect the causal effect of landlockedness, since it could be confounded by the effects of other time-invariant country characteristics (Carrere and Grigoriou, 2008; Paudel et al., 2014). Although these confounding effects could be eliminated by employing panel regressions with country fixed effects, the trouble is that landlockedness is itself time-invariant. Thus, its effect will be purged by country fixed effects along with other time-invariant confounders.[1] Consequently, even though it is intuitive that landlockedness adversely affects trade, there are no causal estimates to show how serious (or not) this problem actually is.

In this paper, we provide the first natural experimental evidence on the causality and persistence of the effect of landlockedness on trade. Our natural experiment comes from the sudden transition of Ethiopia from a *de-facto* coastal country to a *de facto* landlocked one in 1998. Eritrea had been a province of Ethiopia.[2] In 1991, however, pro-independence rebel forces initiated combat and defeated the Ethiopian forces, and Eritrea's independence was secured following a referendum two years later. Despite the *de jure* separation, there was a protocol of understanding between the government of Ethiopia and the newly-formed state of Eritrea for Ethiopia's free and unrestricted use of the Eritrean port of Assab (IMF, 1997; Faye et al., 2004; Briggs and Blatt, 2009; Connell and Killion, 2010). As stated under the intergovernmental transit and port service agreement and customs arrangement of the protocol of understanding, both governments had agreed that Ethiopia would be granted continued free access to the port of Assab with its own customs branch office. Under this agreement, Ethiopia's imports and exports through the port of Assab, which accounted for 95 percent of the country's trade throughput (Briggs and Blatt, 2009; Connell and Killion, 2010), were exempted from Eritrean customs duties and related charges (IMF, 1997). As such, even though Ethiopia was *de jure* landlocked, the port of Assab was practically a *de facto* Ethiopian port within Eritrea.[3]

This arrangement, however, fell apart in 1998 when war broke out between Eritrea and Ethiopia due to border related issues.[4] The escalation of this border-dispute had "taken everybody by surprise, including Ethiopian Prime Minister Meles Zenawi"

[1]To quantify the impact of landlockedness, existing studies typically use a time invariant dummy variable – an indicator of landlockedness - that takes a value of one if a country is landlocked. However, the country fixed effect will partial out the time invariant landlocked indicator, causing the effect of landlockedness to be unidentified.

[2]Eritrea was a colony of Italy from 1998-1941. Following the independence from Italy, British took over the administration from 1941-1952. Eritrea become an autonomous region of Ethiopian and become again province of Ethiopia in 1952 and 1961 respectively.

[3]Ethiopia was a *de jure* landlocked country with coastal access since 1993, but a *de facto* coastal country until 1998.

[4]Both countries disputed over the control of the border town of Badme.

(Abbink, 1998). Due to this conflict, the port of Assab, which is Ethiopia's main commercial outlet to the world, was immediately closed. From that moment on, Ethiopia became truly landlocked. Besides Ethiopia, no other sovereign states in modern times had gone from being a coastal to a landlocked country.

Empirically, we employ two estimation methods to study the treatment effect of landlockedness on trade for Ethiopia. First, we employ a triple difference-in-differences (DDD) approach to estimate the impact of landlockedness on the *bilateral* trade of Ethiopia within a gravity model. Our triple-differencing approach exploits three sources of variation: country variation (landlocked country–Ethiopia– and coastal country–Kenya), product variation (bulky oceanborne freight and light airborne freight) and time variation (before and after "*de facto*" landlockedness).[5] To estimate our gravity model, we used 13 years disaggregated bilateral trade data of the treated and the control countries along with more than 30 common major trading partners of the two countries. The data ranges from 1993 to 2005. In addition, to address the sensitivity of gravity model to the number of variables included in the regression,[6] we control a large set of exporter-year, exporter-product and product-year fixed effects (Magee, 2008; Cheong et al., 2017).

Second, we employ the synthetic control approach to study the impact of landlockedness on the *aggregate* exports and imports of Ethiopia. This method enables us to obtain a data-driven counterfactual, known as a synthetic control, as a weighted average of all the coastal countries in Africa for which data are available.[7] Unlike the conventional approach of choosing a single comparison group, the weighting of the potential control groups (i.e. other coastal African countries) enables the weighted average, which is the synthetic control, to achieve

[5]We define the export of four major ocean-borne products including coffee, leather, vegetable and hide & skin as 'treated' and airborne–gold–as 'control' commodity. Similarly, we define twelve major ocean-borne imports as 'treated' and airborne – medicine and pharmaceutical—as 'control' products

[6]According to Ghosh and Yamarik (2004) and Magee (2008), gravity model is sensitive to the number of variables included in the regression.

[7]We use 34 coastal countries altogether to construct the synthetic control. The list of coastal African countries are Algeria, Angola, Benin, Cameroon, Cape Verde, Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Djibouti, Arab Republic of Egypt, Equatorial Guinea, Eritrea, Gabon, The Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Libya, Madagascar, Mauritius, Morocco, Mozambique, Nigeria, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Tanzania, Togo and Tunisia.

a pre-intervention trend that mirrors Ethiopia's even more closely (See, for example, Abadie et al., 2010; Cheong et al., 2017). More importantly, the synthetic control is data-driven, in the sense that the weights used to construct it are not arbitrarily imposed, but are chosen (based on some loss criteria) so that its characteristics and those of Ethiopia are as similar to each others' as possible.

Our empirical results show that Ethiopia's export and import products are strongly affected by landlockedness. Specifically, landlockedness on average reduces Ethiopian's exports of coffee, leather, crude vegetable and hide & skin by about 43%, 49%, 80% and 72%, respectively. In addition, it reduces Ethiopian's ocean-borne imported goods, such as petroleum, fuel and fertilizer, by 71%, 68.6% and 66.9%, respectively. These large reported effects are robust to various robustness checks, such as placebo test and sub-sample analysis.

To further investigate how persistent the negative effect of landlockedness is, we estimate the size of the treatment effects across years. We find that the effect of landlockedness on Ethiopia's export and import products is not short-lived, but is persistent, to the extent this effect is stronger further down the years for certain goods. The synthetic control method also provides evidence that after the landlockedness shock, there is an increasing divergence between the aggregate exports and imports of Ethiopia and those of the synthetic control. As such, the negative effect of landlockedness on trade is not merely a level effect, but also has an effect on slowing down trade relative to the counterfactual.

Our work is most closely related to the literature that looks at the effect of geographical barriers on trade, especially landlockedness, on the export and import. For example, Radelet and Sachs (1998) studied the effect of geographical isolation and shipping cost on manufactured export and found that the manufacturing exports of landlocked countries are significantly lower than that of coastal countries. Similarly, Limao and Venables (2001), Raballand (2003), Coulibaly and Fontagné (2006), Carrere and Grigoriou (2008), Paudel et al. (2014) and World Bank (2014) argued that landlockedness had a negative impact on trade. To estimate the effect of landlockedness, they estimated the coefficient on a time-invariant landlocked country dummy contained in a cross-sectional cross-country regression. The problem with these results is that they lack a causal interpretation, since it is not possible to disentangle the effects of landlockedness from the effects of other time-invariant country factors, as country fixed effects will partial all of them out. Our work overcomes these issues by providing the first natural experimental evidence on the effects of landlockedness that are estimated from a panel model with a rich fixed effects structure.

Our work is also broadly related to the literature that studies the relationship between trade cost and international trade. Trade economists have long been concerned about the source of trade costs and how they affect trade. A vast literature has attempted to estimate the causal effects of policy barriers (tariffs and non-tariff barriers), transportation (freight costs, time costs), and the effects of the costs associated with the use of different currencies on exports and imports (see Anderson and Van Wincoop, 2004; Disdier and Head, 2008; Christ and Ferrantino, 2011; Djankov et al., 2010; Hummels and Schaur, 2013; Silva and Tenreyro, 2010). In this regard, our paper speaks to this literature by establishing results on the effect of landlockedness, which is a geographical barrier of trade.

The reminder part of the paper is structured as follows. Section (5.2) provides the historical background information about how Ethiopia becomes landlocked in 1998. Section (5.3) discusses the model specification and the estimation method of the study. Section (5.4) describes our data sources and the descriptive statistics of the key variables. Section (5.5) presents the main findings as well as the various robustness checks of the paper; and finally section (5.7) concludes.

5.2 Background

5.2.1 Ethiopia's Access to the Port of Assab

The port of Assab had been Ethiopia's main gateway to the global market. Since the early 1980s, infrastructure additions and reconstructions had been made to improve the port. These included the widening of its harbor, the addition of warehouses

Table 5.1: Time-line for the Independence of Eritrea and the Border War with Ethiopia.

1991	Ethiopian rebels and Eritrea defeat the central government of Ethiopia.
1993	Eritrea becomes independent state.
1998	Eritrean-Ethiopian border war and Ethiopia become *de facto* landlocked.
2000	End of Eritrean – Ethiopian war.

and container berth, the construction of shipyards with ship building capabilities, and the expansion of road transportation infrastructure with the assistance of World Bank, African Development Bank, Norway and China (Fair, 1988). The port had a well-functioning transportation infrastructure, and was connected by 624 km highway to Addis Ababa, the capital city of Ethiopia. At some point in time, it had even accounted for 95 percent of the country's main ocean-borne export and import cargo throughput (Connell and Killion, 2010; Murphy et al., 2013).[8]

Up to the early 1990s, Ethiopia had sovereignty over Assab. However, this changed when the Eritrean People Liberation Front (*EPLF*) and Ethiopian rebel forces from secessionist and dissident groups initiated combat against Ethiopia to establish their full independence and shared government power. After three decades of war against successive governments of Ethiopia, the *EPLF* and Ethiopian rebel forces defeated the Ethiopian central government forces in 1991 (see the time-line in Table 5.1). The defeat of the then government of Ethiopia was followed by a successful referendum for independence among the people of Eritrea, which led to Eritrea's independence in 27 April,1993 (Pool, 1993). Because all of Ethiopia's coastline are located in Eritrea,

[8]Until the federation of Eritrea in 1952, Ethiopia was landlocked country. Its routes to external world was the 780 km railway from Djibouti constructed in 1917. Following federation and then annexation of Eritrea, Ethiopia became a coastal country until 1998.

Ethiopia became *de jure* landlocked and thus lost sovereignty over Assab when Eritrea declared independence.

However, notwithstanding the loss of its coastline, Ethiopia did not become *de facto* landlocked. This is because there was an agreement (a protocol of understanding) between the Transitional Government of Ethiopia (TGE) and the state of Eritrea for Ethiopia's free and unrestricted use of the port of Assab. As stated under an intergovernmental transit and port service agreement and customs arrangement, both governments agreed that Ethiopia would be granted continued free access to the port of Assab with its own Ethiopian customs branch office, and the imports and exports of Ethiopia would remain exempt from Eritrean customs duties and related charges (IMF, 1997; Faye et al., 2004; Connell and Killion, 2010). Thus, the port of Assab was used almost exclusively for export-import trade to Ethiopia's capital city Addis Ababa, the population of Assab was predominantly Ethiopian, the telecommunication system was connected with Ethiopia, and the economy of Assab was entirely built on businesses from Ethiopia (Connell and Killion, 2010).[9] As such, Assab essentially remained an Ethiopian town within Eritrea.

5.2.2 Eritrean-Ethiopian War and the Landlockedness of Ethiopia

This arrangement over the use of port of Assab fell apart on May 6, 1998 when Ethiopia and Eritrea went into war over a border dispute. From then on, the port of Assab was immediately closed to Ethiopia and the country became *de facto* landlocked. With the "closing in" of Ethiopia, it is now the most populous landlocked country in the world, with a population size fast approaching 100 million. Since becoming *de facto* landlocked in 1998, Ethiopia's has redirected its trading routes to a neighboring country, Djibouti, which now handles the great majority of Ethiopia's trade. Unlike trading through the port of Assab, Ethiopia's trade flow is subjected to fees for using the sea ports of other countries and to other related costs associated

[9]Morvover, Port of Assab was purchased by Rubattinio shopping company, Italian company, in 1869 from two Ethiopian sultans prior to the establishment of Eritrea as a region. Hence, Port of Assab can be considered as historical property of Ethiopia.

with the crossing of another sovereign country (Lorton, 2000; Begashaw, 2008).

As discussed, we are primarily interested in the impact that landlockedness might have on development, with trade as the key focus here. Why, then, do we look towards Ethiopia to address this question? Firstly, Ethiopia is the only sovereign country in modern times that had been both coastal and landlocked. Secondly, the availability of trade data before and after the landlockedness for Ethiopia (without Eritrea) enables us to study the causal effect of landlockedness on trade with Ethiopia as an example. Finally, the timing of Ethiopia's *de facto* landlockedness was unanticipated: not only did Ethiopia become *de facto* landlocked, the circumstance that led to its landlockedness caught "everybody by surprise" (Abbink, 1998).[10] Thus, from an econometric perspective, the landlockedness of Ethiopia was a plausibly exogenous shock, which we could use to identify the causal effect of landlockedness.

5.3 Empirical Strategy

Our empirical framework estimates the impact of landlockedness on trade using the gravity model. In its simplest form, the traditional gravity model assumes that trade flows between country i and country j are positively related with the economic size of the two countries and negatively related with their distance.[11] The most widely used standard gravity equation comes from Anderson and Van Wincoop (2003). They show that besides economic size and distance, multilateral resistance terms could also determine trade flows between countries, and these can be controlled for by exporter and importer fixed effects. In this study, we augment the Anderson and Van Wincoop (2003) gravity model by adding an indicator variable that measures the effect of *landlockedness* on trade, and then apply a triple difference-in-differences

[10] Abbink (1998) wrote that The violent Eritrean-Ethiopian border dispute which erupted on May 6 1998 has taken everybody by surprise, including Ethiopian prime minister Meles Zenawi.

[11] Theoretical explanation for the gravity model are provided by (Anderson, 1979; Deardorff, 1998)

estimation approach.[12] Thus, we estimate the following equation:

$$T_{ijkt} = exp(\beta_1 Treat_i * Bulky_k * Post_t + \mu_{it} + \mu_{ik} + \mu_{kt})\varepsilon_{ijkt} \tag{5.1}$$

where T_{ijkt} is either the 3-digit Standard International Trade Classification (SITC) level of import or export flow from country i to country j at time t; $Treat$ is a dummy variable that is equal to 1 for Ethiopia and 0 for Kenya; $Bulky$ is a dummy variable that is equal to 1 for bulky (ocean freight goods) and 0 for light goods that are transported by air freight; $Post$ is a dummy variable that is equal to 1 after 1998 and 0 otherwise. Following the recent literature on gravity models (see, for example, Magee, 2008; Frazer and Van Biesebroeck, 2010; Cheong et al., 2017), we also include a large set of interacted fixed effects, where μ_{it} denotes the export-year fixed effects that subsume the typical gravity regressors (such as changes in exporter's income), and μ_{ik} and μ_{kt} represent the exporter-product and the product-year fixed effects, respectively. Finally, ε_{ijkt} is the idiosyncratic error term of product j traded between countries i and j at time t. We estimate Eq. (5.1) for different sets of import and export sectors. The coefficient on the triple interaction term (β_1) measures the net impact of landlockedness on trade.

Estimation Issues We discuss two key empirical issues and how we take care of them. The first issue comes from that fact that if there are many zeros in the bilateral trade data (which there are), our estimated gravity equation could be biased and inconsistent. This stems from the practice of transforming the gravity equation (e.g. Eq. (5.1) into its log-linear version first, and then estimate the log-linearized gravity equation by OLS. However, to accommodate the modeling of bilateral trade in its log form, we need to drop all country-pair observations with zero trade, since the log of zero is undefined. Consequently, this could cause severe sample attrition.

One stop-gap approach of handling the zero trade problem is to add one dollar to the value of trade ($T_{ijkt} + 1$) before taking the log transformation. However, this procedure is ad-hoc and may still yield inconsistent estimates (Silva and Tenreyro,

[12] Silva and Tenreyro (2010) employs the difference-in-differences approach to estimate the effect of currency union on trade through a gravity model framework.

2006). Moreover, trade data are usually heteroskedastic (Silva and Tenreyro, 2006). The expected value of the log-linearized error term in the gravity equation is likely to be a function of economic size, distance and other multilateral resistance variables, which makes OLS regression inappropriate. To address this issue, we follow Silva and Tenreyro (2006) to estimate Eq. (5.1) using the Poisson Pseudo Maximum Likelihood (PPML) estimator. The PPML estimator estimates Eq. (5.1) in its multiplicative form. Thus, it has the advantage of retaining zero trade values and provides consistent estimates in the presence of heteroskedasticity.[13]

The second issue comes from the fact that the effect of landlockedness of Ethiopia could be confounded by the potential effect of the Eritrean-Ethiopian war. Recall that Ethiopia became (both *de jure* and *de facto*) landlocked after it went into war with Eritrea in 1998. Since both the border war and the landlockedness of Ethiopia occur at the same time, it may be challenging to identify the net effect of landlockedness on trade flows using a pure difference-in-differences analysis.

To address this problem, we take advantage of the variation in the traded products that landlockeness can affect. The idea is the following. The war with Eritrea should affect both ocean-borne and airborne trade of Ethiopia, but landlockedness should affect only ocean-borne trade but not airborne trade. Thus, the change in the trend of ocean-borne trade before and after 1998 should capture the effects of both landlockedness and the war, but the change in the trend of airborne trade before and after 1998 should only capture the effects of the war (i.e. not landlockedness). As such, we could use the latter to partial out the effects of war in the trends of ocean-borne trade. For this reason, we include airborne commodities (light and expensive products) as an additional 'control' group. In doing so, we will have contrast between commodities, countries and time, and therefore, we will estimate the effect of landlockedness on trade by implementing the triple difference-in-differences approach that compares the difference between the export or import of bulky versus light goods of Ethiopia, to the difference in the export or import of bulky versus light

[13]The dependent variables (that include disaggregated import and export) are used without log transformation but the coefficient estimates can be interpreted as elasticities (Silva and Tenreyro, 2006; Paudel and Burke, 2015).

goods of Kenya, before and after 1998.

Besides dealing with the confounding effects of war, the triple-differencing approach also has the advantage of enabling us to partial out differences in trends that have nothing to do with landlockedness. For example, our estimates could be capturing the effects of systematic shocks to ocean-borne and airborne goods that are not associated with the landlockedness. If we include the ocean-borne trade of Kenya as an additional control group, we could partial out the potential divergence of trends in ocean-borne and airborne trade caused by systematic shocks.

More generally, by exploiting variations at the country, year and product levels as our triple-differencing approach does, we could include a rich set of fixed effects, such as exporter-year, exporter-product and product-year, to better identify β. These fixed effects ensure that we are not attributing the influence of year-specific commodity or country traits (shocks) to landlockedness. For example, following Ethiopia's landlockeness, exporter of bulky commodities may enjoy new infrastructure such as roads that may affect bulky and light commodities differently. Such potential confounder, however, could be controlled for by product-year fixed effect. Similarly, the two exporting countries-Ethiopia and Kenya may experience country-specific institutional or policy changes during the treatment period. To partial out the effects of country-specific policies or shocks, as well as the effects of all country-specific factors for trade, we could control for exporter-year fixed effects.[14] Finally, the possibility of referential trade policies on products may affect exports differently. Such confounding effects could also be dealt with by exporter-product fixed effects.

5.4 Data

The data for this analysis is taken from the UN Comtrade database. We use bilateral export and import data of bulky (ocean-borne) and light (airborne) commodities of Ethiopia and Kenya between 1993 and 2007.[15] The import and export data are

[14]The country-year fixed effects also capture the effect of exporters' change in GDP, income per capital, population and other gravity variables.

[15]We use 33 major trading partners of Ethiopia and Kenya to construct the bilateral panel data set. We also use the data from 1993-2010 for the synthetic control regression.

constructed using mirror data as these are likely to be more accurate in a developing country context (Paudel and Burke, 2015).[16] The data used in the analysis is at the one-digit (aggregated) and three-digit (disaggregated) Standard International Trade Classification (SITC).

For ocean-borne exports, we consider four major ocean-borne export products including coffee, leather, vegetable and hide & skin, which will be our "treated" goods. For the airborne exports, we consider gold, which will be our "control" good.

For ocean-borne imports, we consider fertilizer, fuel, petroleum, chemicals, iron and steel, metal, industrial machines, special machines, rubbers, transportation, textile, dyeing, perfume, and miscellaneous manufacturing materials. Like before, these ocean-borne imports will be our "treated" goods. For airborne imports, we consider light commodities such as medicine and pharmaceutical products, which will be our "control" goods. Data on the exports and imports of these goods for Ethiopia (without Eritrea) prior to the closure of Assab port are available for 1993-1997.

5.5 Triple-Differencing Analysis

5.5.1 Landlockedness and Export

A. Baseline

Table 5.2 presents the triple difference-in-differences estimation results for the different major export products. Columns (1)-(4) report the effect of landlockedness on coffee, leather, crude vegetable (that includes natural gums, resins, cut flowers, gum resins and other similar export products), and hide and skin export, respectively. For these results, we have included exporter-year, exporter-product and product-year fixed effects into the model. For inference, we report robust standard errors that are adjusted for two-way clustering by exporter and product.

Column (1) reveals that landlockedness has a large negative and statistically significant effect on Ethiopia's coffee export. Specifically, the estimated coefficient

[16]Export from Ethiopia and Kenya is constructed from the import by largest trading countries. Similarly, the import from Ethiopia and Kenya are constructed form Export reported by major trading partners

Table 5.2: The Effect of Landlockedness on Disaggregated Export

	Types of export item			
	Coffee	Leather	Crude Vegetable	Hide & skin
	(1)	(2)	(3)	(4)
Treat × Bulky × Post	-0.561***	-0.681***	-1.589***	-1.271***
	(0.014)	(0.091)	(0.050)	(0.130)
Fixed Effects				
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	1560	1560	1560	1560
Pseudo R^2	0.085	0.022	0.069	0.041

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's export products and zero for Kenya's export products; ***bulky*** is 1 for ocean-borne exports and zero for light (air-borne) export product (i.e. export of gold); and ***Post*** is 1 after 1998 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

on the triple interaction term shows that coffee exports are reduced by about 43% following the landlockedness of Ethiopia, on average.[17] This 43% reduction in coffee exports is significant: coffee faming provides the livelihood income of 15 million Ethiopians (Moat et al., 2017) and coffee exports account for a quarter (i.e. 25%) of Ethiopia's export earnings. Hence, through a back-of-the-envelop calculation, a 43% reduction in coffee exports translates into a 11% (i.e. 25% × 43% ≈ 11%) decline in total export earnings. This is just coffee alone: the total negative effects of landlockedness are likely to be much larger.

Columns (2), (3) and (4) also show that lack of access to the Assab port reduces Ethiopia's export of leather, crude vegetable, and hide and skin by 49%, 80% and 72%, respectively. All these estimates are statistically significant at 1%. Overall, the negative effects of landlockedness observed here appears to be larger than the negative effects reported in the previous studies. These studies usually estimate the effect of landlockedness by estimating the coefficient on the landlocked dummy. As such, they cannot deal with confounding factors like country fixed effects. For example, Limao and Venables (2001) finds that a median landlocked country trades 28% less than a

[17]The formula to compute the effect of a dummy variable in a PPML model is $(e^{\theta_i} - 1) \times 100\%$, where θ_i is the estimated coefficient of dummy variable i (Silva and Tenreyro, 2006).

maritime country. In addition, Paudel et al. (2014) shows that landlocked developing countries (LLDCs) export about 25% less than other least developing countries. By contrast, our study shows that for the ocean-borne goods considered, landlockedness has caused exports to decline by about 50% or more.

B. Placebo test for export

Next, we conduct a placebo test for our baseline results in Table 5.2. The placebo test evaluates the effect of landlockedness on export before Ethiopia actually became a *de facto* landlocked country in 1998. If our identification strategy in Table 5.2 is valid, then landlockedness should not have any statistically significant effects before 1998. As such, we employ 1996 as a false treatment year (i.e. placebo), and present the triple-differenced estimate of its effect on the four major export items of Ethiopia in Table 5.3.[18] Across all columns, we find that the placebo is statistically insignificant. Thus, there is good evidence that our baseline estimate is capturing the effect of landlockedness and not other coincidental events.

Table 5.3: Placebo: the Effect of Landlockedness on Disaggregated Export

	Types of export item			
	Coffee	Leather	Crude Vegetable	Hide & skin
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-0.110 (0.322)	-0.380 (0.328)	0.169 (0.326)	-0.648 (0.490)
Fixed Effects				
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	600	600	600	600
Pseudo R^2	0.070	0.083	0.024	0.058

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's export products and zero for Kenya's export products; ***bulky*** is 1 for ocean-borne exports and zero for light (air-borne) export product (i.e. export of gold); and ***Post*** is 1 for 1996 and 1997; and 0 for 1993 to 1995. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Importer country level clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[18] Therefore, the pre-treatment period is from 1993-1995 and the false treatment period is from 1996-1997.

C. The dynamic effect of landlockedness on export

Previously in Section A., we estimate the average effect of landlockedness on exports during the treatment period. However, such an estimate does not tell us if the negative effects of landlocked is short-lived or persistent.[19] In this section, we investigate how persistent the negative effect landlockedness is. To do so, we interact the triple-difference term with year dummies (Frazer and Van Biesebroeck, 2010), and compare the exports in each treatment year with the exports in the pre-treatment years to track the evolution of the effect of landlockedness on exports overtime.

In Table 5.4, we report the year-by-year effects of landlockedness on Ethiopia's coffee exports (Column (1)), leather exports (Column (2)), crude vegetable exports (Column (3)), and hide & skin exports (Column (4)). All the coefficients of the quadruple interaction term show that the average effect of landlockedness is persistent. Thus, the effect of landlockedness does not appear to be short-lived. That being said, there is also no evidence that the negative effect of landlockedness is becoming stronger over time.

D. Restricting the sample countries

To obtain the results reported earlier, we have used data on thirty three major trading partners of both the treated country (i.e. Ethiopia) and the control country (Kenya) to investigate the effect of landlockedness on export. It is well known that estimates from the gravity model are potentially sensitive to the sample of countries included in the analysis (Haveman and Hummels, 1998; Magee, 2008).[20] As a robustness check, we re-estimate the model using data on exports with Ethiopia's and Kenya's top 20, 15 and 10 trading partners.

In Table 5.5, we only include the top 20 most important trading partners of the two countries. As before, we find that landlockedness has a negative and statistically significant effect on the exports of Ethiopia. These results continue to hold when

[19] There is a presumption that landlockedness has long-lasting negative impacts on trade and economic development (Arvis et al., 2010; World Bank, 2014).

[20] Haveman and Hummels (1998) shows the effect of Regional Trade Agreements (RTA) on trade is sensitive to change in sample of countries used in the analysis: the impact of of RTA varies when the sample of countries in the regressions is changed.

Table 5.4: The Dynamic Effect of Landlockedness on Export

	Types of export item			
	Coffee	Leather	Crude Vegetable	Hide & skin
	(1)	(2)	(3)	(4)
DDD × D_1998	0.318***	-0.651***	-0.524***	-0.138***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_1999	0.534***	0.787***	-0.624***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2000	-0.767***	-0.904***	-1.321***	-1.191***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2001	-2.236***	-1.792***	-1.692***	-1.638***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2002	-3.129***	-2.951***	-2.836***	-2.589***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2003	-1.959***	-1.406***	-1.916***	-1.625***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2004	-2.044***	-1.263***	-2.098***	-2.032***
	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2005	-1.716***	-0.546***	-1.748***	-2.021***
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed Effects				
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Observations	1560	1560	1560	1560
Pseudo R^2	0.085	0.069	0.019	0.040

Note: $\boldsymbol{DDD} \equiv \boldsymbol{Treat} * \boldsymbol{bulky} * \boldsymbol{Post}$. $\boldsymbol{Treat}$ is an indicator variable that equals 1 for Ethiopia's export products and zero for Kenya's export products; $\boldsymbol{bulky}$ is 1 for ocean-borne exports and zero for light (air-borne) export product (i.e. export of gold); and $\boldsymbol{Post}$ is 1 after 1998 and zero otherwise. $\boldsymbol{D\_year}$ is a dummy variable that equals 1 for that specific $\boldsymbol{year}$ and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Importer country level clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

restrict our sample to the top 15 or 10 trading partners (see Table A1 and Table A2 in Appendix A). Hence, the impact of landlockedness on export is similar to the baseline in terms of sign and statistical significance, and is not sensitive to the number of trading partners considered in the analysis.

Table 5.5: The Effect of Landlockedness on Disaggregated Export: Top 20 Partner Countries

	Types of export item			
	Coffee	Leather	Crude Vegetable	Hide & skin
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-0.650***	-0.722***	-1.653***	-1.222***
	(0.017)	(0.089)	(0.051)	(0.130)
Fixed Effects				
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	1430	1430	1430	1430
Pseudo R^2	0.079	0.026	0.067	0.047

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's export products and zero for Kenya's export products; ***bulky*** is 1 for ocean-borne export and zero for light (air-borne) export product (i.e. export of gold); and ***Post*** is 1 after 1998 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5.2 Landlockedness and Import

A. Baseline

In this section, we look at the effect of landlockedness on Ethiopia's ocean-borne imports. For each of the major imports, we re-estimate Eq. (5.1) by replacing the dependent variable, which was exports, with the imports from the major trading partners. The key variable of interest is once again "$Treat \times Bulky \times Post$" and the coefficient on the triple-interaction term measures the the effect of landlockedness on Ethiopia's ocean-borne imports.

In Columns (1)-(16) of Table 5.6, we find that all the coefficients of "$Treat \times Bulky \times Post$" are negative and statistically significant, suggesting that landlockedness reduces the major imports. The difference in the magnitude of the estimates across the product types indicates the presence of heterogeneity in how landlockedness affects imports. For example, landlockedness severely affects the import of petroleum, mineral fuel and fertilizer,[21] but has a smaller impact on the import of general industrial machinery, machinery specialized for particular industries and inorganic chemicals.

[21] According to the point estimates, landlockedeness reduces the import of petroleum, fuel and fertilizer by 71%, 68.6% and 66.9%, respectively.

Table 5.6: The Effect of Landlockedness on Different Import Goods

	Types of import item							
	Fertilizer	Fuel	Petroleum	Chem_material	Chem_related	Dyeing	Perfume	Inorganic_chem
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × bulky × Post	-1.106***	-1.161***	-1.264***	-0.389***	-0.256***	-0.370***	-0.135***	-0.085***
	(0.028)	(0.081)	(0.086)	(0.018)	(0.007)	(0.018)	(0.016)	(0.028)
Importer × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1456	1456	1456	1456	1456	1456	1456	1456
Pseudo R^2	0.196	0.078	0.079	0.125	0.272	0.165	0.152	0.171

	Types of import item							
	Rubber	Textile_yarn	Metal	Iron_steel	Mis_manu	Special_machinery	Indus_machinery	Road_vehicle
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treat × bulky × Post	-0.674***	-0.399***	-0.329***	-0.239***	-0.257***	-0.062***	-0.063***	-0.085***
	(0.027)	(0.016)	(0.019)	(0.013)	(0.013)	(0.011)	(0.016)	(0.020)
Importer × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1456	1456	1456	1456	1456	1456	1456	1456
Pseudo R^2	0.116	0.048	0.080	0.040	0.101	0.064	0.084	0.051

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's import products and zero for Kenya's import products; ***bulky*** is 1 for ocean-borne imports and zero for light (air-borne) import products (i.e. import of medicine and pharmaceutical products); and ***Post*** is 1 after 1998 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similarly, landlockedness has also a detrimental effect on the import of foreign raw materials and intermediate inputs in manufacturing sector. In our regression, we find that landlocked status reduces import of rubber, steel, textile yarn and dyeing by 49%, 21%, 32.9% and 30.9%, respectively. This reduction may have a large implication for firms in the manufacturing sector as technology may diffuse through the used of imported intermediate inputs. Kasahara and Rodrigue (2008), for example, show that foreign inputs improves productivity through learning, variety and quality effects. Amiti and Konings (2005) also argue that importing foreign intermediaries raise firm's productivity.

Overall, the strong adverse effects on almost all major imports support the argument that landlockedness is indeed a serious impediment to access global markets (see, for example, Limao and Venables, 2001; Faye et al., 2004; Djankov et al., 2010; Christ and Ferrantino, 2011).

B. Placebo for import

The key identification assumption in our estimation is that in the absence of landlockedness, there should be no difference in the trends between the imports of ocean-borne and airborne cargo. Using import data from 1993 to 1997, we perform a falsification test, in which we assume that Ethiopia was landlocked in 1996 (i.e. a placebo) instead of 1998. Table 5.7 presents the estimation results, where the coefficients on the triple-interaction term are statistically insignificant. This suggests that the effect on imports post-1998 is not a placebo effect.

Table 5.7: Placebo: the Effect of Landlockedness on Different Import Goods

	Types of import item			
	Fertilizer	Fuel	Petroleum	Chem_material
	(1)	(2)	(3)	(4)
Treat × bulky × Post	0.316	0.347	0.312	0.119
	(0.364)	(0.274)	(0.300)	(0.195)
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	560	560	560	560
Pseudo R^2	0.156	0.056	0.062	0.074
	Types of import item			
	Chem_related	Metal	Road_vehicle	indust_machinery
	(5)	(6)	(7)	(8)
Treat × bulky × Post	0.286*	0.200	0.143	0.400
	(0.168)	(0.277)	(0.241)	(0.256)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	560	560	560	560
Pseudo R^2	0.212	0.043	0.068	0.072

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's import products and zero for Kenya's import products; ***bulky*** is 1 for ocean-borne imports and zero for light (air-borne) import products (i.e. import of medicine and pharmaceutical products); and ***Post*** is 1 after 1996 and zero before 1996. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Importer-product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C. The dynamic effect of landlockedness on import

Table 5.8 presents the year-by-year effects of landlockedness on imports. The strong negative effect of landlocked status on import does not disappear; instead the impact of landlockedness increases significantly over time for certain goods. For example, landlockedness has reduced the import of fertilizer from 14% to 88.6%; mineral fuel from 41.7% to 71.7% and petroleum from 41.6% to 71.6%. For fertilizer, petroleum and mineral fuel, the impact of landlockedness during the last year of our sample (88.6%, 71.7% and 71.6%) is larger than the average effect of landlockedness measured over the previous eight years period (68.6%, 71% and 66.7%, from Table 5.6). This is consistent with the presumption that landlockedness has persistent negative effect on trade.

Table 5.8: The Dynamic Effect of Landlockedness on Import

	Types of import item							
	Fertilizer	Fuel import	Petroleum	Chem_material	Chem_related	Textile_yarn	Road_vehicle	Mis_manu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DDD × D_1998	-0.151***	-0.541***	-0.538***	-0.374***	-0.243***	-0.135***	-0.343***	-0.227***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_1999	-1.070***	-0.241***	-0.236***	-0.061***	-0.167***	-0.133***	0.397***	0.193***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2000	-1.010***	-0.584***	-0.581***	-0.121***	-0.272***	-0.288***	-0.038***	-0.050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2001	-2.110***	-1.211***	-1.210***	-0.559***	-0.352***	-0.513***	-0.683***	-0.309***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2002	-1.372***	-1.447***	-1.478***	-0.825***	-0.549***	-0.448***	-0.905***	-0.391***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2003	-1.320***	-1.251***	-1.589***	-0.474***	-0.413***	-0.153***	-0.522***	-0.337***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2004	-1.848***	-1.433***	-1.434***	-0.941***	-0.496***	-0.602***	-0.867***	-0.356***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DDD × D_2005	-2.173***	-1.263***	-1.259***	-1.329***	-0.618***	-0.818***	-1.507***	-0.797***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Importer × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1456	1456	1456	1456	1456	1456	1456	1456
Pseudo R^2	0.196	0.065	0.066	0.124	0.272	0.048	0.050	0.101

Note: $\boldsymbol{DDD \equiv Treat * bulky * Post}$. ***Treat*** is an indicator variable that equals 1 for Ethiopia's imports and zero for Kenya's imports; ***bulky*** is 1 for ocean-borne import and zero for light (air-borne) import product; and ***Post*** is 1 after 1998 and zero otherwise. ***D_year*** is a dummy variable that equals 1 for that specific ***year*** and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Importer country level clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D. Restricting sample countries

We re-estimate our model by restricting the number of trading partners. Table 5.9 reports the triple-difference analysis using only 20 main trading partners and shows that the sign and statistical significance of the triple interaction term are unchanged from the baseline. In Table B1 and B2 of Appendix B, we conducted further robustness checks by restricting the sample to 15 and 10 main trading partners and find that our results are not sensitive to the selection of major trading partners for the analysis.

Table 5.9: The Effect of Landlockedness on Different Import Goods: with Top 20 Partners

		Types of import item		
	Fertilizer	Fuel	Petroleum	Chem_material
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-1.306***	-1.416***	-1.537***	-0.447***
	(0.036)	(0.121)	(0.128)	(0.021)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	1040	1040	1040	1040
Pseudo R^2	0.242	0.096	0.097	0.151
		Types of import item		
	Chem_related	Textile_yarn	Road_vehicle	Mis_manu
	(5)	(6)	(7)	(8)
Treat × bulky × Post	-0.341***	-0.556***	-0.272***	-0.387***
	(0.011)	(0.025)	(0.016)	(0.017)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	1040	1040	1040	1040
Pseudo R^2	0.329	0.057	0.072	0.124

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's import products and zero for Kenya's import products; ***bulky*** is 1 for ocean-borne imports and zero for light (air-borne) import products (i.e. import of medicine and pharmaceutical products); and ***Post*** is 1 after 1996 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Exporter-product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.6 Synthetic Control Analysis

For the previous results, we have used Kenya, a neighboring coastal country, as a comparison. In this section, we implement the synthetic control approach, a data-driven approach that enables us to construct comparison group from the set of possible comparisons that mirrors Ethiopia's pre-intervention trend as closely as possible. To construct the comparison group, we take weighted sum of the export (import) of the 34 coastal African countries as follows:

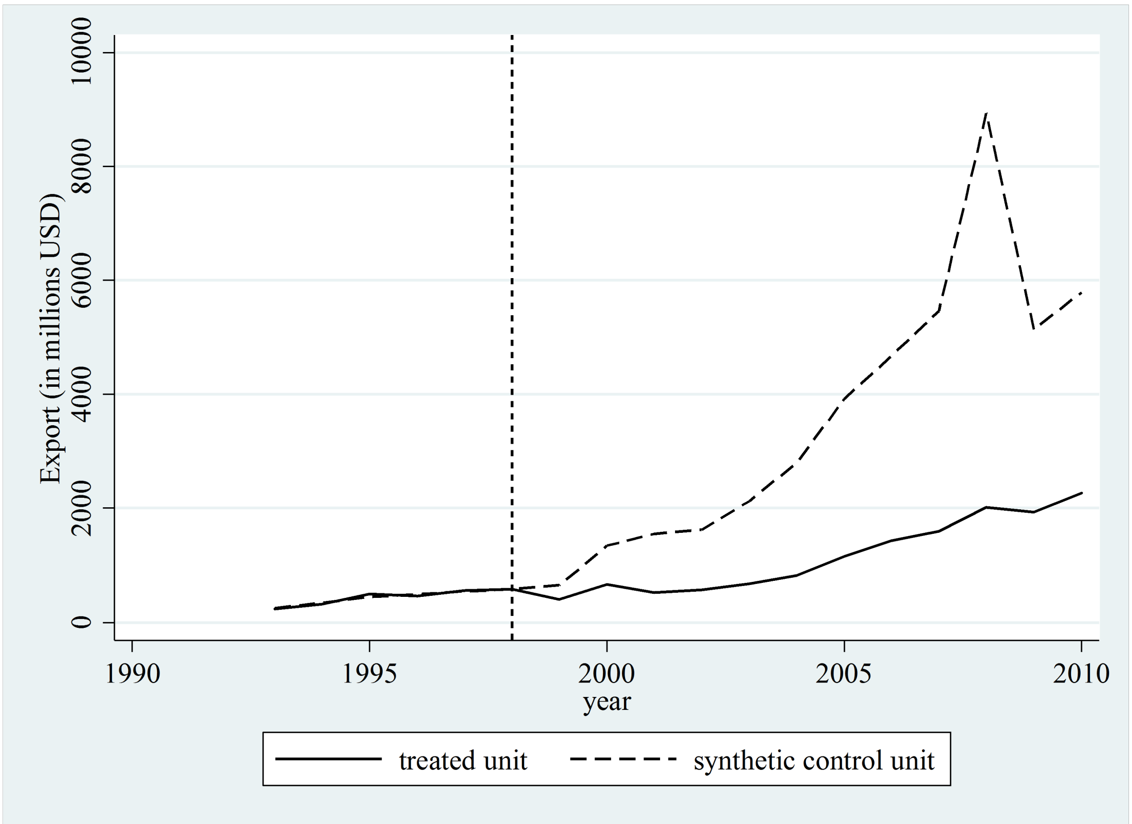
$$\widehat{T}_t = \sum_{j \epsilon c} \omega_j T_{jt} \tag{5.2}$$

where $\widehat{T}_t$ is the synthetic control for annual aggregate Ethiopia's export (import) in year t. T_{jt} is the period t aggregate annual export (import) of the 34 coastal African countries; and ω_j is the weight to coastal country c (note that: $\sum \omega_j = 1$ and $\omega_j \geq 0$). The weights are calculated by minimizing the mean squared errors of the export (import) of the landlocked country (T_{it}) with the coastal country (T_{jt}) in the pre-landlocked period (*i.e.* from 1993-1997) as follows:

$$\omega_j = arg\ min \sum_{t=1993}^{1997} (T_{it} - \omega_j T_{jt})^2 \tag{5.3}$$

Figure 5.1 plots the aggregate annual exports of Ethiopia and the synthetic control. The export of the synthetic control nearly perfectly matches the export of Ethiopia before 1998 (the start of the treatment period). However, after Ethiopia becomes both *de facto* and *de jure* landlocked, the total exports of the synthetic control increase dramatically and reaches at its highest level in 2007 (during the start of the great financial crisis period), while for Ethiopia, total exports decline immediately after being landlocked and remain low for a long-period of time. A benefit of using the synthetic control approach is that it provides a visual examination of the progress of the effect of the treatment (i.e. landlockedness). As shown in Figure 5.1, the difference in the exports of Ethiopia and the synthetic control has widen over time since 1998. This, again, suggests that landlockedness has a long-lasting effect.

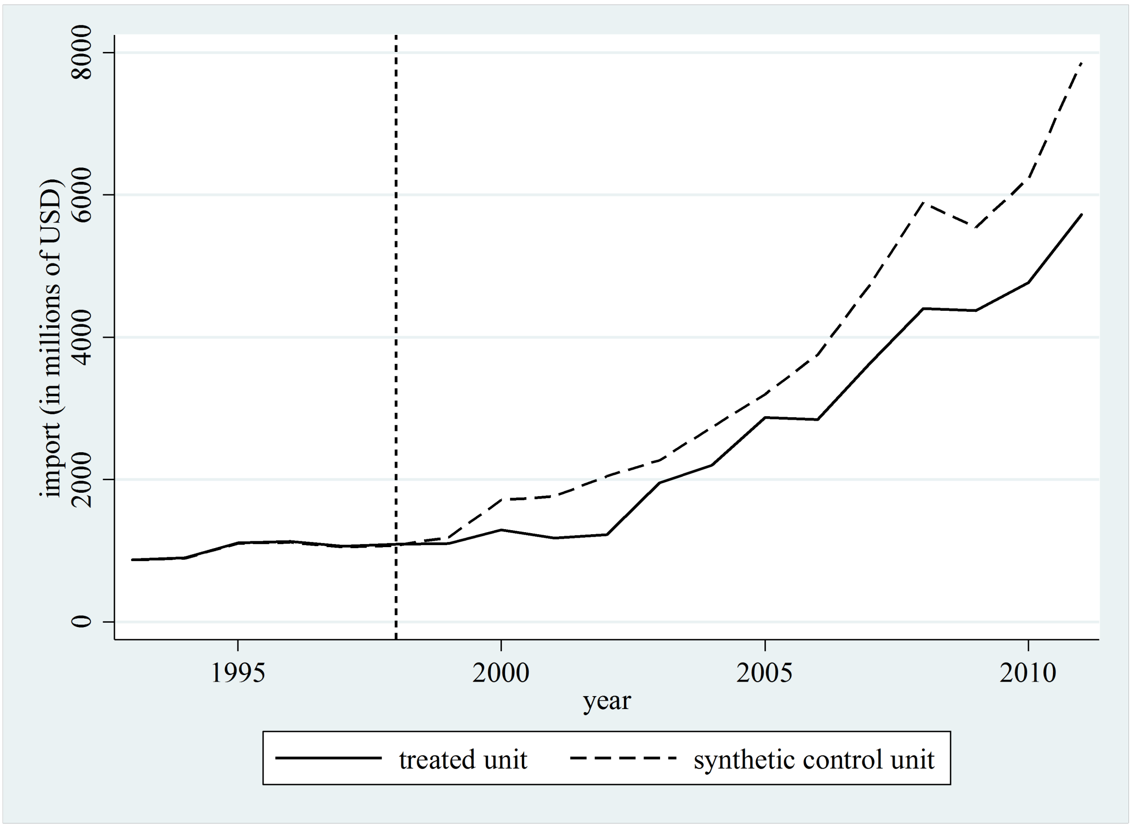
Figure 5.1: The Effect of Landlockedness on Aggregate Export



Note: This figure shows the synthetic control plot of the effect landlockedness on Ethiopia's total export. Ethiopia's export is the treated group and we take the export of 34 African coastal countries in the potential control group. The treatment period starts in 1998 –as shown by the vertical dotted line.

Similarly, Figure 5.2 shows the impact of landlockedness on Ethiopia's imports. The dotted line plots the total imports for the synthetic control and the unbroken line plots the total imports of Ethiopia. Just as before, the imports of the synthetic control and Ethiopia are nearly identical before the treatment. However, from 1998 onwards, Ethiopia's imports have lagged far behind the synthetic control's. This suggests that landlockedness has a negative effect on the volumes of Ethiopia's imports. Although the divergence is not as large as that for exports, the effect of landlockedness on import is nonetheless persistent across time.

Figure 5.2: The Effect of Landlockedness on Aggregate Import



Note: This figure shows the synthetic control plot of the effect of landlockedness on Ethiopia's total import. Ethiopia's import is the treated unit and the import of 34 African coastal countries as the potential control group. The treatment period starts in 1998 –as shown by the vertical dotted line.

5.7 Conclusion

Landlocked developing countries are among the poorest of developing countries. The limited participation in the international markets, due to typical high cost of trade, is often presumed to be one of the main contributors towards poverty experienced by these countries. In this chapter, we estimate the impact of landlockedness on trade and examine how it evolves over time. To do so, we use the natural experiment of Ethiopia becoming *de facto* landlocked following its war with Eritrea in 1998. We find that landlockedness has a negative and statistically significant effect on the export and import of ocean-borne products. Moreover, we find that the negative effects of landlockedness on both exports and imports are long-lasting. From a policy perspective, it will be important for the international community to provide assistance to landlocked developing countries given that the negative effects of landlockedness are large and persistent.

References

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of Californias tobacco control program. *Journal of the American statistical Association 105*(490), 493–505.

Abbink, J. (1998). Briefing: the Eritrean-Ethiopian border dispute. *African Affairs 97*(389), 551–565.

Amiti, M. and J. Konings (2005). Trade liberalization, intermediate inputs and productivity: Evidence from Indonesia.

Anderson, J. E. (1979). A theoretical foundation for the gravity equation. *The American Economic Review 69*(1), 106–116.

Anderson, J. E. and E. Van Wincoop (2003). Gravity with gravitas: a solution to the border puzzle. *The American Economic Review 93*(1), 170–192.

Anderson, J. E. and E. Van Wincoop (2004). Trade costs. *Journal of Economic literature 42*(3), 691–751.

Arvis, J.-F., G. Raballand, and J.-F. Marteau (2010). *The cost of being landlocked: logistics costs and supply chain reliability.* World Bank Publications.

Begashaw, G. (2008). Port of Assab as a factor for economic development and regional conflict.

Briggs, P. and B. Blatt (2009). Ethiopia: Bradt travel guides.

Carrere, C. and C. Grigoriou (2008). Landlockedness, infrastructure and trade: new estimates for Central Asian countries.

Cheong, J., D. W. Kwak, and H. Yuan (2017). Trade to aid: EU's temporary tariff waivers for flood-hit Pakistan. *Journal of Development Economics 125*, 70–88.

Christ, N. and M. J. Ferrantino (2011). Land transport for export: The effects of cost, time, and uncertainty in sub-Saharan Africa. *World Development 39*(10), 1749–1759.

Connell, D. and T. Killion (2010). *Historical dictionary of Eritrea*, Volume 114. Scarecrow Press.

Coulibaly, S. and L. Fontagné (2006). South–south trade: geography matters. *Journal of African Economies 15*(2), 313–341.

Deardorff, A. (1998). Determinants of bilateral trade: does gravity work in a neoclassical world? In *The regionalization of the world economy*, pp. 7–32. University of Chicago Press.

Disdier, A.-C. and K. Head (2008). The puzzling persistence of the distance effect on bilateral trade. *The Review of Economics and statistics 90*(1), 37–48.

Djankov, S., C. Freund, and C. S. Pham (2010). Trading on time. *The Review of Economics and Statistics 92*(1), 166–173.

Fair, D. (1988). Ports and harbours: the ports of Djibouti and Assab: changing fortunes. *Africa Insight 18*(2), 93–95.

Faye, M. L., J. W. McArthur, J. D. Sachs, and T. Snow (2004). The challenges facing landlocked developing countries. *Journal of Human Development 5*(1), 31–68.

Frazer, G. and J. Van Biesebroeck (2010). Trade growth under the African growth and opportunity act. *The Review of Economics and Statistics 92*(1), 128–144.

Ghosh, S. and S. Yamarik (2004). Are regional trading arrangements trade creating?: An application of extreme bounds analysis. *Journal of International Economics 63*(2), 369–395.

Haveman, J. and D. Hummels (1998). Trade creation and trade diversion: New empirical results. *Journal of Transnational Management Development 3*(2), 47–72.

Hummels, D. L. and G. Schaur (2013). Time as a trade barrier. *The American Economic Review 103*(7), 2935–2959.

IMF (1997). *Selected Issues: Eritirea.* International series of monographs on physics. IMF.

Kasahara, H. and J. Rodrigue (2008). Does the use of imported intermediates increase productivity? plant-level evidence. *Journal of development economics 87*(1), 106–118.

Limao, N. and A. J. Venables (2001). Infrastructure, geographical disadvantage, transport costs, and trade. *The World Bank Economic Review 15*(3), 451–479.

Lorton, F. (2000). The Ethiopia-Eritrea conflict: a fragile peace. *African Security Review 9*(4), 101–111.

Magee, C. S. (2008). New measures of trade creation and trade diversion. *Journal of International Economics 75*(2), 349–362.

Moat, J., J. Williams, S. Baena, T. Wilkinson, T. W. Gole, Z. K. Challa, S. Demissew, and A. P. Davis (2017). Resilience potential of the Ethiopian coffee sector under climate change. *Nature Plants 3*(7), nplants201781.

Murphy, S. D., W. Kidane, and T. R. Snider (2013). *Litigating War: Mass Civil Injury and the Eritrea-Ethiopia Claims Commission*. Oxford University Press.

Paudel, R. C. et al. (2014). Export performance in developing countries: A comparative perspective. Technical report.

Paudel, R. C. and P. J. Burke (2015). Exchange rate policy and export performance in a landlocked developing country: The case of Nepal. *Journal of Asian Economics 38*, 55–63.

Pool, D. (1993). Eritrean independence: The legacy of the derg and the politics of reconstruction. *African Affairs 92*(368), 389–402.

Raballand, G. (2003). Determinants of the negative impact of being landlocked on trade: an empirical investigation through the Central Asian case. *Comparative economic studies 45*(4), 520–536.

Radelet, S. and J. Sachs (1998). Shipping costs, manufactured exports, and economic growth. In *American Economic Association Meetings, Harvard University, mimeo.*

Silva, J. S. and S. Tenreyro (2006). The log of gravity. *The Review of Economics and statistics 88*(4), 641–658.

Silva, J. S. and S. Tenreyro (2010). Currency unions in prospect and retrospect. *Annual Review Economics 2*(1), 51–74.

World Bank (1998). World development indicators.

World Bank (2014). Improving trade and transport for landlocked developing countries: A ten-year review. Technical report.

Appendix A: Landlockedness, Export and Import: Restricting the Partner Countries

Table A1: The Effect of Landlockedness on Disaggregated Export: Top 15 Partner Countries

	Types of export item			
	Coffee	Leather	Crude Vegetable	Hide & skin
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-0.658***	-0.745***	-1.676***	-1.243***
	(0.016)	(0.093)	(0.051)	(0.142)
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	1430	1430	1430	1430
Pseudo R^2	0.079	0.026	0.067	0.047

Note: ***Treat*** is a dummy that equals 1 for Ethiopia's exports and zero for Kenya's exports; ***bulky*** is 1 for ocean-borne and zero for light export; and ***Post*** is 1 after 1998 and 0 otherwise. Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: The Effect of Landlockedness on Disaggregated Export: Top 10 Partner Countries

	Types of export item			
	Coffee	Leather	Crude Vegetable	Hide & skin
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-0.341***	-0.909***	-2.165***	-1.241***
	(0.021)	(0.088)	(0.078)	(0.142)
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	1300	1300	1300	1300
Pseudo R^2	0.086	0.026	0.065	0.060

Note: ***Treat*** is a dummy that equals 1 for Ethiopia and zero for Kenya's exports; ***bulky*** is 1 for ocean-borne exports and zero for light export; and ***Post*** is 1 after 1998 and 0 otherwise. Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B: Landlockedness and Import: Restricting the Partner Countries

Table B1: The Effect of Landlockedness on Different Import Goods: with Top 15 Partners

	Types of import item			
	Fertilizer	Fuel	Petroleum	Chem_material
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-0.726***	-1.792***	-1.804***	-0.452***
	(0.047)	(0.168)	(0.167)	(0.023)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	780	780	780	780
Pseudo R^2	0.294	0.111	0.110	0.184

	Types of import item			
	Chem_related	Textile_yarn	Road_vehicle	Mis_manu
	(5)	(6)	(7)	(8)
Treat × bulky × Post	-0.265***	-0.512***	-0.294***	-0.414***
	(0.012)	(0.025)	(0.017)	(0.020)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	780	780	780	780
Pseudo R^2	0.329	0.068	0.089	0.140

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's import products and zero for Kenya's import products; ***bulky*** is 1 for ocean-borne import and zero for light (air-borne) import products (i.e. import of medicine and pharmaceutical products); and ***Post*** is 1 after 1996 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Exporter-product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: The Effect of Landlockedness on Different Import Goods: with Top 10 Partners

	Fertilizer	Fuel	Petroleum	Chem_material
		Types of import item		
	(1)	(2)	(3)	(4)
Treat × bulky × Post	-0.852***	-0.783***	-0.783***	-0.399***
	(0.132)	(0.082)	(0.080)	(0.047)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	520	520	520	520
Pseudo R^2	0.393	0.255	0.255	0.244

	Chem_related	Textile_yarn	Road_vehicle	Mis_manu
		Types of import item		
	(5)	(6)	(7)	(8)
Treat × bulky × Post	-0.201***	0.026	-0.292***	-0.451***
	(0.030)	(0.041)	(0.024)	(0.040)
Importer × Year	Yes	Yes	Yes	Yes
Importer × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Observations	520	520	520	520
Pseudo R^2	0.434	0.072	0.127	0.171

Note: ***Treat*** is an indicator variable that equals 1 for Ethiopia's import products and zero for Kenya's import products; ***bulky*** is 1 for ocean-borne import goods and zero for light (air-borne) import products (i.e. import of medicine and pharmaceutical products); and ***Post*** is 1 after 1996 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (5.1). Exporter-product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 6

Agricultural Commodity Exchange and Trade in Developing Countries: Evidence from a Quasi-natural Experiment

Dessie Tarko Ambaw   Habtamu Tesfaye Edjigu

School of Economics, The University of Adelaide

Statement of Authorship

Title of Paper	Agricultural Commodity Exchange and Trade in Developing Countries: Evidence from a Quasi-natural Experiment
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
Publication Details	The paper is written in publication style for submission to a journal.

Principal Author

Name of Principal Author (Candidate)	Dessie Tarko Ambaw		
Contribution to the Paper	Contributed to planning the article and the methodology, conducted the literature review, collected the data, analysed and interpreted the results, wrote part of the manuscript.		
Overall percentage (%)	50%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that ~~would~~ constrain its inclusion in this thesis. I am the co-author of this paper.		
Signature		Date	06/09/2018

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Habtamu Tesfaye Edjigu		
Contribution to the Paper	Contributed to planning the article and the methodology, conducted the literature review, collected the data, analysed and interpreted the results, wrote part of the manuscript and acted as the corresponding author.		
Signature		Date	06/09/2018

Abstract

Would developing countries benefit from having a commodity exchange? We consider this question by studying its effects on coffee exports in Ethiopia. Coffee farming is the most important agricultural activity in Ethiopia, as it supports the livelihood of 15 million farmers and generates a quarter of the country's export. In April 2008, the government of Ethiopia introduced the Ethiopian Commodity Exchange (ECX) to provide reliable market information and storage facilities to farmers, especially coffee producers, and to help them engage in the export industry. Using a triple-differencing (DDD) approach, we find that the introduction of coffee trading through the ECX has led to a significant increase in Ethiopia's coffee export. We also find that the ECX has led to export coffee into new foreign markets. Our paper is related to recent initiatives by governments and international organizations to introduce agricultural commodities exchanges in developing countries. We provide quasi-natural experimental evidence to show that such initiatives can help to reduce market-related barriers of trade faced by these countries.

Key Words: Commodity Exchange, Ethiopian Coffee Export, Triple Differences

JEL Codes: D47, Q13, F14, F6

6.1 Introduction

Many developing countries rely on the exports of agricultural commodities sector as a main source of national income (Reardon and Timmer, 2007; World Bank, 2008; Gollin, 2010).[1] However, in these countries, there are also structural issues that prevent markets for agricultural commodities from functioning well. For example, agricultural producers require reliable price information, sound contractual agreements, and extended marketing chains, which these countries lack (Gabre-Madhin and Goggin, 2005; Mutenyo, 2011; Gabre-Madhin, 2012)(Tiffin and Irz, 2006; Byerlee et al., 2009; Islam, 2016). Moreover, they also require strong institutions to protect themselves from being exploited by intermediaries (Gabre-Madhin, 2001; Gabre-Madhin and Goggin, 2006; Goyal, 2010). Without strong institutions, the profitability of farmers, their incentives to produce, and consequently their export earnings could be curtailed (UNCTAD, 2009; Goyal, 2010).

It has been argued that these structural challenges can be addressed with the help of an agricultural commodity exchange, which is a centralized market place where sellers and buyers meet to transact commodities in an organized fashion (UNCTAD, 2009). Modern commodity exchange platforms, for instance, may eliminate exploitative intermediaries, provide more transparency on the prevailing market price to farmers, and ultimately, promote agricultural production and exports. For this reason, governments and international organizations have worked together to introduce agricultural commodities exchanges in their own countries, which they hope would reduce such market-related barriers.[2] Empirically, while it seems intuitive that commodity exchanges would help the agricultural commodities sectors, we do not have strong evidence that developing countries would benefit from having a commodity exchange, especially when it is an advanced market mechanism.

In this paper, we exploit a quasi-natural experiment to study how having a

[1]Different studies illustrate that agriculture is the primary source of income in developing countries. For example, 65% of the labor force is employed in agriculture (World Bank, 2008). Moreover, for African and South Asian countries, the share of agricultural output to GDP exceeds 40% and agricultural export constitute 15-30% of GDP (World Bank, 2008; Gollin, 2010).

[2]For example, UNCTAD is working with the African Union, with national governments and the private sector to develop agricultural commodity exchanges. Many emerging countries such as India, Brazil, China, Malaysia and the South Africa have also introduced modern commodities exchanges.

commodity exchange affects coffee exports in Ethiopia. In April 2008, the Ethiopian government introduced a commodities exchange market, called the Ethiopian Commodity Exchange (ECX), to replace the country's traditional coffee auction floor.[3] The ECX provides several services to facilitate coffee transactions. For instance, it provides daily market information through electronic display boards (ticker boards) to coffee producing villages, where information are disseminated using Interactive Voice Response (IVR), message services (SMS) and through the ECX's website. It also provides warehouses across the country that facilitate storage and quality testing. Finally, the ECX facilitates standard trading contracts and payments through its partner settlement banks. These services raise the profitability of coffee farming and motivate the farmers to produce larger quantities of higher quality coffee for the export market.

To estimate the effect of the ECX on the coffee exports of Ethiopia, we implement a triple difference-in-differences (DDD) approach within a gravity framework. For identification, the triple differencing approach has certain advantages over the standard difference-in-differences (DD) approach. If we implement the latter, we could only compare the treatment and control between commodities (for the same country) or between countries (for the same commodity). For example, a commodity-level DD would look at the exports of coffee (the treatment) and non-ECX commodities (the control) from Ethiopia and compare how their trends before and after the establishment of the ECX. However, such a comparison may falsely attribute the effects of macroeconomic shocks on coffee to the ECX, if these shocks and the ECX occurred at the same time. Similarly, a country-level DD approach would consider the exports of coffee from Ethiopia (the treatment) and Kenya (the control) and compare the response of their coffee exports before and after the establishment of the ECX. However, such a comparison may also falsely attribute a response in Ethiopia's coffee exports, caused by factors such as institutional reforms and infrastructural improvements, to the ECX.

[3] Ethiopian coffee farmers are now required to sell their coffee at designated primary markets, where only certified buyers are allowed to make purchases. Similarly, coffee processors must receive approval to use designated warehouses, where their products are graded based on whether they are suitable for the export market or are only for sale in the domestic market.

The triple-differencing approach addresses these issues by comparing the difference between the exports of coffee (an ECX product) and a non-coffee product (a non-ECX product) of Ethiopia to the difference between the exports of coffee and a non-coffee product of Kenya.[4] Because the triple difference exploits country-commodity-year variations in exports, we may employ fixed effects with more complex structures to deal with potential confounders that a standard DD approach cannot deal with. Here, we follow Magee (2008) and Cheong et al. (2017) to include the full set of country-pair, exporter-year, exporter-product, product-year, and importer-year fixed effects into our gravity model.[5]

Our estimates show that as a policy, the establishment of the ECX has been an effective means for promoting exports. Specifically, Ethiopia has seen an 84% increase in coffee exports on average after the ECX was established. This impact is twice as large as the impact of joining regional trade agreements, trade concessions, and importer tariff reductions.[6] Our estimates also show that the establishment of the ECX does not have spillover effects on non-ECX products, in the sense that while the ECX has led to a significant increase in Ethiopia's coffee export, there is no evidence that it has reduced the exports of a non-ECX commodity. Finally, our results show that the ECX not only affects coffee exports along the intensive margin, but it also has a statistically significant impact on coffee exports along the extensive margin.

This paper makes two contributions. Firstly, it speaks to the debate on whether a commodity exchange is effective for promoting exports in developing countries. Besides Ethiopia, commodity exchanges have been actively promoted and developed in other African countries such as South Africa, Zambia, Malawi, and Uganda

[4]We consider Kenya as a control country since this country is the largest coffee Arabica exporter in Africa. Kenya has also no functional agricultural commodities exchange.

[5]According to Ghosh and Yamarik (2004) and Magee (2008), the gravity model is sensitive to the choice of different covariates. Magee (2008) demonstrate that controlling a whole set of fixed effects in the gravity model allows to capture the different determinants of trade. For example, importer-exporter fixed effects helps to capture all unobserved time-invariant factors that affect the bilateral trade between two countries. Similarly, importer-year fixed effects capture all time-invariant and time-varying characteristics of the importer country, such as GDP per capital and population.

[6]For example, Frazer and Van Biesebroeck (2010) show that export may increase by as much as 40% due to US trade concession policy for Africa (also known as AGOA), and Cheong et al. (2017) shows that Pakistan export increases by around 45% following a temporary removal of tariff.

(Sitko and Jayne, 2012). Hence, the performance of these commodity exchanges on raising agricultural export deserves systematic investigation using quasi-experimental approaches. For Ethiopia, the ECX potentially affects over 4.2 million smallholder farmers and more than a quarter of the countrys export earnings,[7] but its effect on export is not empirically investigated. While a commodity exchange seems to be useful for promoting exports, some have argued that an exchange is an advanced market mechanism that only functions well in industrialized countries.[8] The differing views on this issue, however, are based mainly on anecdotal evidence. Therefore, our paper hopes to provide some statistical evidence to shed light on this issue.

Secondly, our paper contributes to the literature methodologically by providing quasi-natural experimental evidence on the impact of the commodity exchange in the developing countries context. The original ECX project was aimed at facilitating the exchange of food grains including wheat, maize and beans. However, the world food crisis adversely affected the domestic grain market, and led to a tripling of prices. The slowdown of trading food grains, which is an external shock, resulted in the introduction of coffee trading into the exchange. Therefore, the introduction of coffee in the ECX platform was not pre-meditated, but was driven by events that affected food supply.[9] It is in this regard that the ECX is the best quasi-natural experiment for studying the impact of a commodity exchange in the developing countries context.

The rest of the paper is structured as follows. Section 6.2 provides background on Ethiopian Commodities Exchange. Section 6.3 describes the empirical strategy. Section 6.4 describes the data. Section 6.5 and section 6.6 present the results, and finally section 6.7 concludes.

[7]See Minten et al. (2014) and Craparo et al. (2017) for more detail.

[8]For example, Sitko and Jayne (2012) have shown that the performance of agricultural commodity exchanges in Africa is poor because of the limited success in attracting financial institutions to the modern market platform, conflict of interest among brokers, and the high fixed costs of trading in the commodity exchanges. In fact, Van der Mheen-Sluijer (2010) has expressed doubts on the ECX's success in achieving the demands of coffee importers. Ethiopian coffee exporters were also complaining about issues of price-meddling by government authorities (Ferreira et al., 2017).

[9]A program is endogenous when the program itself is non-random and/or when the program participants are non randomly selected

6.2 Background

A. Coffee Market in Ethiopia

Ethiopia has a long history in coffee production and is now the largest coffee producer in Africa.[10] Coffee is also the main export commodity of Ethiopia. It contributes to nearly 25 percent of the country's total export and supports the livelihood of more than 15 millions of people (Moat et al., 2017). Therefore, policy makers in Ethiopia look towards coffee production as a means of raising smallholders income, government revenue, and foreign currency (Petit, 2007).

Prior to 1991, the coffee market in Ethiopia was regulated by the government through its agency, Ethiopia Coffee Market Corporation (ECMC). During this time, the government tightly controlled the trade and price of coffee. Farmers in the main coffee growing area were given a certain quota to supply coffee, at a fixed price, to the government (through the ECMC). The Central Bank of Ethiopia also sets the minimum export price while the Ministry of Coffee and Tea determined the domestic price (Petit, 2007; Gemech and Struthers, 2007; Andersson et al., 2017).

Following the dismantling of Ethiopia's socialist regime in 1991, the transitional government undertook market reforms that affected coffee production and marketing. For example, the ECMC was closed, the coffee market was deregulated, and license fees and tariffs for coffee trading were reduced. The export price controls and local coffee price floors were also abolished (Petit, 2007). All these reforms were made to encourage and expand the private sector's participation in the coffee market, and to stimulate production and improve export earnings from coffee (Gemech and Struthers, 2007).

However, while these reforms had led to a larger number of private firms in the coffee trade, little had changed in the marketing and distribution of coffee and other agricultural products (Gabre-Madhin and Goggin, 2006). In fact, prior to the establishment of the ECX, coffee farmers often did not know what the prevailing retail price in different markets and the price offered by wholesalers or exporters were. This

[10]For example, Ethiopia is believed to be the origin of coffee Arabica.

gave rise to exploitative intermediaries or middlemen, who were well informed about the market price, to buy coffee from smallholders farmers at lower prices and sell them to wholesaler or exporters at higher prices. The lack of reliable price information in other markets had also limited the farmers' bargaining power in price negotiation. Moreover, the farmers also faced high risk of default as there were limited legal means of enforcing contracts. For example, Gabre-Madhin (2012) showed that 67% traders faced contractual default. To manage such risk, trade was limited to short distance markets and confined to network of family members, friends and ethnic connection, which made the sector unprofitable to invest in (Gabre-Madhin, 2001). Therefore, weak infrastructure and market institutions, which affected the marketing and distribution of coffee, had limited the potential scale of coffee production and export in Ethiopia (Gabre-Madhin, 2001; Gabre-Madhin and Goggin, 2005).

B. The Ethiopian Commodity Exchange

The establishment of the Ethiopian Commodity Exchange (ECX) was preceded by a series of events unrelated to the coffee industry. In 2000 and 2001, Ethiopia had a bumper crop, mostly grains, which led to a 60 to 80 percent drop in price of these surplus goods (Gabre-Madhin, 2012). Because of weak market systems and transportation costs, the surplus agricultural production were not transported and distributed to regions that had relatively less supply, which curtailed farmers' profits of harvesting grains in those years. As such, many were unable to pay for fertilizers, which led to a cut-back on fertilizer use,[11] and consequently, a significant decline in agriculture production in the following year (Gabre-Madhin, 2012). This series of events culminated into a major food crisis, which subjected 14 million Ethiopians to potential famine, highlighted the need for Ethiopia to adopt a modern agricultural commodities marketing and distribution system (Gabre-Madhin, 2001).

Faced with such risk, the Ethiopian government launched a modern market system – the ECX – in 2008. The ECX started with a spot trading and "open outcry" bidding system, which was appropriate for the level of technology and institutional system

[11]Farmers were unable to pay for fertilizer. Thus, fertilizer use was reduced by 27 percent.

of the country at that time. The original ECX project was aimed to facilitate the trading of food grains including wheat, maize and beans. However, the world food crisis adversely affected domestic grain price, causing it to rise by 200 percent in June 2008. The slowdown of food grains trade resulted in the introduction of coffee to the exchange and the suspension of Ethiopia's traditional coffee auction floor.[12]

Coffee trade has benefited from three main services provided by the ECX. Firstly, the ECX provides daily market information through electronic display boards (ticker boards) to coffee producing villages. In addition, information is disseminated using Interactive Voice Response (IVR), short message services (SMS) and through the ECX website. Secondly, it provides warehouses for storage and to facilitate quality testing of coffee supplied by coffee producing villages. Thirdly, the ECX facilitates standard trading contracts and payments through its partner settlement fbanks. The main rationale for introducing the ECX is to avoid exploitative intermediaries (i.e. the middlemen), increase farmers' revenue and production, ultimately, to raise export earnings.

The ECX is successful in many aspects. For example, after the ECX was established, coffee farmers were able to receive up to 70% of the final export price than the 38% they had received prior to the ECX (Gabre-Madhin, 2012). In 2011, the total value of the ECX trade reached USD 1.1 billion and the ECX expanded its number of warehouses to 55 with a total capacity of 250,000 tons.

The ECX had also settled USD 20 million or more on T+1 (next day) basis with no single default. They also now disseminate market price information through their outdoor electronic ticker boards located in 32 rural sites, through their website that attracts visitors from over 107 countries, and directly to their 256,000 mobile subscribers, radio, TV and print media (Gabre-Madhin, 2012). The ECX enables farmers to make both production and marketing decision on the basis of information. In particular, they will help farmers know the quality grading of their product

[12]With the help of international donors such as Agency for International Development, the Canadian International Development Agency, the World Bank, the International Fund for Agricultural Development, the United Nations Development Programme, World Food Program and the European Union, *Eleni Gabre-Madhin* was the main driving force behind the successful establishment of the Ethiopia Commodity Exchange (Gabre-Madhin, 2012; Andersson et al., 2017).

and the price premium they will earn from improving the quality of their coffee (Gabre-Madhin, 2012). All of these services may help to promote production and increase export earnings.

6.3 Empirical Strategy

To evaluate the impact of the establishment of the Ethiopian Commodities Exchange (ECX) on coffee export, we estimate the following triple difference-in-difference (DDD) specification within a gravity framework:

$$Export_{ijkt} = exp[\beta_1 Treat_i \times ECX_k \times Post_t + \mu_{it} + \mu_{ik} + \mu_{kt} + \mu_{ij} + \mu_{jt}]\varepsilon_{ijkt} \quad (6.1)$$

where $Export_{ijkt}$ is export value of coffee from country i to country j during year t. Country i denotes either Ethiopia or Kenya; whereas country j represents the top trading partners of Ethiopia or Kenya.[13] $Treat_i$ is in an indicator variable that takes the value of 1 if the country is Ethiopia (the "treated" country) and 0 for Kenya (the "control" country). ECX_k is an indicator variable that takes a value 1 for coffee (the ECX commodity) and 0 for non-ECX commodities including flower, fruit & vegetable, spices, leather and hide & skin. $Post_t$ is a binary variable that switches from 0 before 2008 to 1 from 2008 on wards for both countries and products.

In our model, we take advantage of the disaggregated nature of our export data to include a rich set of fixed effects that accounts for differences across time, countries (i.e. importers and exporters) and products (i.e. ECX and non ECX products). In Eq. (6.1), μ_{it} is a set of export-year fixed effects that subsume the typical gravity regressors (such as such as importer and exporter GDP and multilateral resistance terms); μ_{ik} is exporter-product fixed effects that captures, for example, exporters preferential trade policies on products that may affect commodity exports differently; μ_{kt} is a set of product-year fixed effects that controls for potential commodity specific

[13]The thirty-three major trading partners of the two country are Austria, Belgium, Brazil, Bulgaria, Canada, China, Egypt Arab Rep., France, Germany, Greece, India, Iran Islamic Rep., Israel, Italy, Japan, Korea Rep., Kuwait, Malaysia, Morocco, Netherlands, Pakistan, Romania, Russian Federation, Saudi Arabia, South Africa, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Arab Emirates, United Kingdom, and United States.

time varying factors; μ_{ij} represent the exporter-importer fixed effects to account for unobserved factors such as bilateral distance, language etc. The remaining term, ε_{ijkt}, is the error term.

The coefficient of interest (i.e. β_1) captures the average impact of the ECX on coffee exports of Ethiopia. To estimate Eq. (6.1), we use Poisson pseudo-maximum likelihood (PPML) estimation proposed by Silva and Tenreyro (2006). The PPML approach has several methodological advantages over the common OLS estimation, which involves the log-linearization of Eq. (6.1) and then estimating the parameters of the log-linearized model. Firstly, log-linearizing the gravity equation will alter the properties of the error term, such that the conditional expectation of the *log of the error term* (i.e $E(ln\varepsilon_{ijct})$) will be a function of the regressors, which could cause the estimates to be inconsistent (Silva and Tenreyro, 2006). Secondly, the log-transformation of the gravity equation requires data with zero bilateral trade to be dropped. For a typical developing country such as Ethiopia, there are many zero bilateral trade values. Thus, we will lose a large amount of data if drop the zeros. Importantly, the zeros are themselves informative. If we parse our bilateral trade data to those with positive values, this could generate a sample section problem that could bias our OLS estimates. For these reasons, it will be more appropriate to estimate the multiplicative form of the gravity equation using the PPML approach (Silva and Tenreyro, 2006, 2010).

Threats to Identification of the ECX: We highlight some concerns related to identifying the impact of the ECX on the exports of coffee in Ethiopia. While some of this concerns are common to all impact evaluation analysis, some are specific to the ECX program.

Obtaining a Counterfactual: The first challenge in estimating the impact of the ECX on the coffee exports of Ethiopia is to identify the appropriate counterfactual group. We consider a neighboring country, Kenya, as the control since it is the second largest African country that produces and exports Coffee Arabica but does not have a commodity exchange. However, country-level difference-in-differences model may falsely attribute a change in Ethiopia's coffee export, caused by factors such as institutional reforms and infrastructural improvement, to the ECX. To address this concern, we add non-ECX commodities (flowers, fruits and vegetables, hide and skin, leather and spices) as an additional control group. Hence, we estimate the impact of the ECX on coffee exports using the triple differences (DDD) approach. The triple difference approach by comparing the difference between export if coffee (and ECX product) and other products (non-ECX products) of Ethiopia to the different between the exports of coffee and other commodity product of Kenya. Because triple difference exploits country-commodity-year variations in exports, we are able to control fixed effects to deal with potential confounding factors (Frazer and Van Biesebroeck, 2010).

Parallel Trends: One of the main assumption for the validity of our identification is that the change in export over time would have been the same across coffee and other commodities, in the absence of the EXC. Using coffee exports data between 2003 to 2007, we perform a placebo test that falsely assumes 2006 as the starting period of the ECX. In addition, we test the parallel trend assumption by comparing trends in the exports of non-ECX commodities in Ethiopia and Kenya using data for the whole sample period (2003-2013). The trends in the exports of non-ECX commodities of both countries should follow the same trend regardless of the ECX.

Idiosyncratic or Covariate Shocks: The second issue comes from the fact that when estimating β_1, there are potential confounding factors. During the sample period, there could be improvements in infrastructure, irrigation and trade facilitation that could increase production and exports of coffee in Ethiopia. Without addressing this possibility, we may falsely attribute these potential benefits to the ECX itself. To address this issue, we include product-year fixed effects in Eq. (6.1) that partial out all confounding time-varying or invariant factors affecting coffee exports.

In addition, the two coffee exporting countries– Ethiopia and Kenya – may experience other institutional or policy reforms during the treatment period that affects their coffee exports differently. To address this concern, we include exporter-year fixed effects in Eq. (6.1) that capture the effects of aggregate shocks on coffee export. These dummies also capture changes in GDP, income per capita, population and other aggregate variables that affect coffee exports in both countries. We have also added exporter-product fixed effect to control for the possibility of exporters preferential trade policies on product types that may affect different products export differently.

Importers of Ethiopian coffee may also experience positive or negative idiosyncratic shocks that affect Ethiopia's coffee export. If these potential shocks coincide with the ECX, the estimated effect of the ECX on exports may not reflect the true impact. To address this issue, we include importer-year fixed effects in Eq. (6.1) that eliminate the confounding effects of shocks to the importing countries. Similarly, we also include the exporter-year fixed effect, as it takes care of all exporter specific factors of exports – observed or unobserved, time-varying or time-invariant – such as the exporter's institution, GDP, per capita income and population. Furthermore, we include importer-exporter fixed effects to partial out all characteristics between the importer and exporter that affect how much they trade.

6.4 Data

We use data on exports of Ethiopia and Kenya to their common major trading partners (Appendix A provides the full list of the major trading partners of the two countries) for the period between 2003 and 2011. The export flow data is taken from the UN Comtrade data base. If export flow is not reported in a given year, it is set be zero during that particular year. For the model capturing the extensive margin, we create a dummy dependent variable that is equal to 1 for non-zero exports and 0 if otherwise.

Table 6.1 presents the summary statistics of the data. Columns (1) and (2) report the mean and standard deviation of Ethiopia's exports of agricultural commodities including coffee, flower, spice and fruit and vegetable. Furthermore, Columns (3) and (4) present the mean and standard deviation of Kenya's exports of the same commodities. The summary statistics shows that the average coffee exports of Ethiopia ($441,503,400) is higher than the average coffee exports of Kenya ($96,931,500) for the 2003-2013 period. Moreover, Ethiopia average exports of hide

Table 6.1: Summary Statistics

	Ethiopia		Kenya	
	Mean	Std. Dev.	Mean	Std. Dev.
Product	(1)	(2)	(1)	(2)
Coffee	441503.4	241646.6	96931.5	59316.7
Flower	54109.8	30328.3	367741.9	250960
Fruit and vegetable	95992.1	41469.3	221969.8	104748.9
Hide and skin	9438.3	9211.7	3889.9	3744.1
Leather	48349.8	23024.9	20358.9	9208.5
Spices	82825.5	1152.8	4895.7	3516.8
All agricultural products	169862.6	213051.9	120638.1	160419.5
All manufacturing products	26049.02	22284.46	24199.5	23330.3

Note: All the summary statistics values are in thousands ('000) of US dollar. All agricultural products include coffee, flower, spices and fruit & vegetable. Similarly all manufactured products include leather and hide & skin.

& skin, leather and spices are larger than Kenya. The last two rows of Table 6.1 report the average exports of agricultural and manufactured products of the two countries. The average export values indicate that Ethiopia and Kenya generate nearly equal amount of of revenue from the exports of agricultural and semi-processed manufactured goods in the sample period.

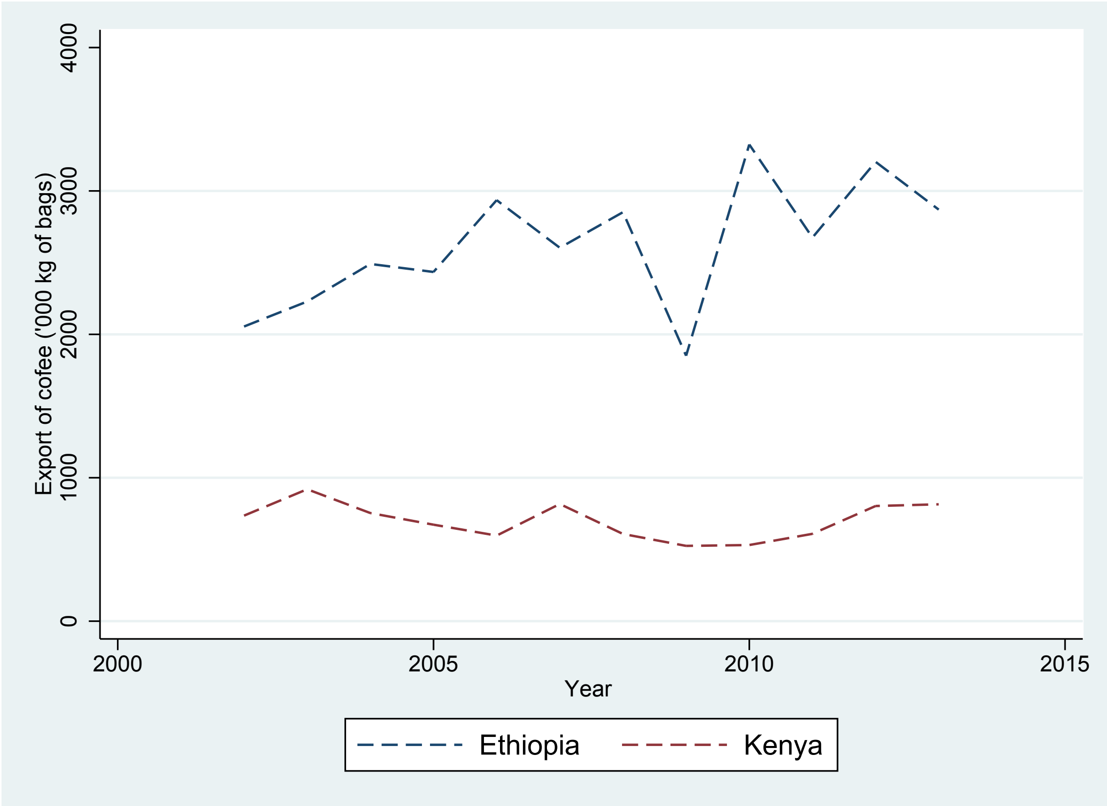
Figure 6.1 presents the time series plots of coffee exports for Ethiopia and Kenya during 2003-2013. The blue dotted line shows the quantity of coffee exports for Ethiopia and the red dotted line shows the quantity of coffee exports for Kenya. These two plots show that the trends in coffee exports before the introduction of the ECX were quite similar for both countries. However, the trend of Ethiopia's coffee exports shows a significant increase following the establishment of the ECX. This suggests that the introduction of the ECX has led to an increase in Ethiopia's coffee export.

6.5 Results

6.5.1 Baseline

Table 6.2 presents the triple difference (DDD) estimates of the impact of the ECX on Ethiopia's coffee export, based on Eq. (6.1). In Column (1), we include the exporter-year, exporter-product, and product-year fixed effects. In Column (2) we

Figure 6.1: Coffee Exports: Ethiopia versus Kenya



Note: This figure shows the aggregate exports of coffee for Ethiopia and Kenya in thousands of 60 kg bags.

add importer-exporter fixed effects. In Column (3), we include all the above fixed effects. In all specifications, exporter-product clustered robust standard errors are reported in parentheses.

In all specifications, the coefficient of interest (i.e. $Treatment \times ECX \times Post$) is positive and statistically significant at 1%. In particular, the ECX increase Ethiopia's coffee exports by 84%.[14] From the policy perspective, this large effect has significant implication for the following reasons. Firstly, coffee exports accounts a quarter (i.e. 25%) of Ethiopia's export earning. Hence, the 84% increase in coffee exports represents a 21% (i.e. $25\% \times 84\% \approx 21\%$) boost in total export for Ethiopia. Secondly, coffee faming provides a livelihood for 15 million Ethiopians (Moat et al., 2017). We would therefore expect an increase in coffee exports to have a positive social economic impact in Ethiopia. Finally, the magnitude of the coefficient indicates that market reform in developing country could have higher effect than joining regional trade

[14]The formula to compute the effect of a dummy variable in a PPML model is $(e^{\beta_i} - 1) \times 100\%$, where β_i is the estimated coefficient of dummy variable i (Silva and Tenreyro, 2006).

Table 6.2: The Impact of the ECX on Coffee Export: Intensive Margin

	(1)	(2)	(3)
Treatment × ECX × Post	0.616***	0.616***	0.616***
	(0.047)	(0.047)	(0.047)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	No	Yes	Yes
Importer × Year	No	No	Yes
Observations	3564	3564	3564
Pseudo R^2	0.079	0.721	0.771

Note: Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). ***Treatment*** is an indicator variable that is equal 1 for Ethiopia's exported products and 0 for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other five exported products (i.e. flower, fruit & vegetable, spices, leather, and hide & skin); and ***Post*** is 1 after 2008 and zero otherwise. Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

agreements, trade concessions, and importer tariff reductions. For example, Frazer and Van Biesebroeck (2010) show that US trade concession policy for Africa (also known as AGOA) increases export by about 40% and Cheong et al. (2017) finds that temporary removal of tariff following a natural disaster increases Pakistani export by around 45%. These responses are only about one-half of the increase in coffee exports, which follows from the introduction of coffee to the ECX platform.

6.5.2 Robustness Checks

In this section we examine the robustness of our results by performing five checks consists of placebo test, alternative estimation method, alternative control groups and assessments based on restriction of trading partners in the gravity model.

A. Placebo test

The main assumption required for the internal validity of our triple differenced approach is the parallel trend assumption. This assumption requires that both treated and control groups have the same trends if the treatment had not occurred. Hence, we examine whether or not the exports of coffee (the treated group) and the other commodities (the control group) had parallel trends before the introduction of the

ECX, we falsely assume 2006 to be the treatment year (i.e the introduction of the ECX) and estimate the model using only pre-treatment data ranges from 2003 to 2007 (because there is no treatment during these years).

Table 6.3 presents the results from the placebo test. In Column (1), we control for the exporter-year, exporter-product and product-year fixed effects. In Column (2), we control for importer-exporter fixed effects. In Column (3), we control for all the interactive fixed effects. The estimated coefficients of the placebo tests are all statistically insignificant. This suggests that there are nothing else, besides the ECX, that had caused the ECX and non-ECX products to have divergent trends.

Table 6.3: The Impact of ECX on coffee exports with False Treatment Year

	(1)	(2)	(3)
Treatment × ECX × Post-2005	0.200	0.200	0.200
	(0.131)	(0.131)	(0.131)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	No	Yes	Yes
Importer × Year	No	No	Yes
Observations	1584	1584	1584
Pseudo R^2	0.061	0.697	0.704

Note: Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). Year 2006 is used as false treatment period to check the validity of our identification strategy. Hence, ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other five exported products (i.e. flower, fruit & vegetable, spices, leather, and hide & skin); and ***Post* − 2005** is 1 for 2006 and 2007 and zero otherwise. Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B. Alternative estimation method

The question of how to estimate gravity model is not trivial. Our baseline results in Table 6.2 are based on Poisson pseudo maximum likelihood (PPML) estimation. This approach provides consistent estimates in the presence of conditional heteroskedasticity caused by log-linearizing the gravity model. However, its downside is that it is a nonlinear regression approach; thus, it is not suitable for estimating models with a large number of fixed effects (Magee, 2008).[15] To check if our baseline result is an artifact of the estimation approach chosen, we re-estimated the model using ordinary least squares (OLS) regression, which allows us to control for many fixed effects in the model.

Table 6.4: The Impact of the ECX on Coffee Exports: OLS Estimates

	(1)	(2)	(3)
Treatment × ECX × Post	1.170***	1.170***	1.170***
	(0.141)	(0.143)	(0.148)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	No	Yes	Yes
Importer × Year	No	No	Yes
Observations	3564	3564	3564

Note: OLS is used to estimate Eq. (6.1) using $\boldsymbol{log(1 + Export_{ijkt})}$ as the dependent variable. ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other five exported products (i.e. flower, fruit & vegetable, spices, leather, and hide & skin); and ***Post*** is 1 after 2008 and zero otherwise. Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The OLS results, provided in Table 6.4, show that the coefficients on $Treatment \times ECX \times Post$ are positive and statistically significant at 1% level.[16] Therefore, there is no evidence that the statistical significance of our baseline results is dependent on the estimation method chosen.

C. Restricting the control (non-ECX) commodities

In the baseline results, our control group (non-ECX commodities) consists of both agricultural items (flower, spices, fruit and vegetable) and non-agricultural items (leather, hide and skin) that are not traded via the ECX. However, there may be a concern that factors such as agricultural policy may affect the exports of coffee and agricultural commodities more uniformly than the exports of non-agricultural commodities. Thus, by including non-agricultural commodities into our regression,

[15] For example, although it is infrequent, the PPML estimator automatically excludes some of our fixed effects (due to collinearity) in our baseline model which might be a bit concerning.

[16] Notably, the OLS estimates are quite large compared to the PPML estimates of Table 6.2. This results are consistent with the evidence documented by Silva and Tenreyro (2006) that OLS overestimates the effect of trade attributes in gravity model due to misspecification issues.

Table 6.5: Using only Agricultural Goods as Control Group

	(1)	(2)	(3)
Treatment × ECX × Post	0.661***	0.661***	0.661***
	(0.044)	(0.044)	(0.044)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	No	Yes	Yes
Importer × Year	No	No	Yes
Observations	2376	2376	2376
Pseudo R^2	0.067	0.735	0.787

Note: ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other three agricultural exported products (i.e. flower, fruit & vegetable, and spices); and ***Post*** is 1 after 2008 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this may accentuate the contrast between coffee and non-coffee exports after the ECX was established. Therefore, the non-agricultural commodities in our control group could be responsible for the statistical significance of the ECX.

To reduce such potential contrast between coffee and non-ECX commodities, we restrict the control group to agricultural commodities only. Table 6.5 shows that the impact of ECX on coffee exports remains positive and statistically significant at 1% significance level. This suggests that our baseline results are not driven by the inclusion of non-agricultural commodities into the control group.

D. Varying the sample of trading partners

In the baseline regressions (Table 6.2), we have used data on bilateral coffee and non-coffee exports of Ethiopia and Kenya to 33 major trading partners. One concern about the gravity model is that its estimates are potentially sensitive to the sample of trading partners included in the analysis (Magee, 2008). For example, Haveman and Hummels (1998) have shown that the effect of Regional Trade Agreements (RTA) on trade is sensitive to the sample of trading partners used in the analysis. When the number of the sample countries is changed, the effects of RTA vary dramatically as well.

Here, we explore if our baseline results are robust to the use of different sample countries. As a robustness check, we have re-estimated our model using the top 20, 15 and 10 trading partners and with all the interactive fixed effects (i.e. exporter-year, exporter-product, product-year, importer-exporter and importer-year fixed effects). In Table 6.6, Columns (1)-(3) present the estimation results associated with the use of the top 20, 15 and 10 trading partners, respectively. Based on these results, we find that the magnitude of the estimated coefficient of the triple interaction term increases when we reduce the number of trading partners. In addition, the estimated coefficients of the triple interaction term are positive and statistically significant at least at 5% significance level. This suggests that the statistical significance of the ECX for exports is not driven artificially by the sample of countries

Table 6.6: The Impact of ECX on Coffee Export: Using Different Top Trading Partners

	(1)	(2)	(3)
	Top 20 partners	Top 15 partners	Top 10 partners
Treatment × ECX × Post	1.046***	1.177***	1.190**
	(0.252)	(0.216)	(0.589)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	Yes	Yes	Yes
Importer × Year	Yes	Yes	Yes
Observations	2160	1590	1060
Pseudo R^2	0.793	0.800	0.867

Note: ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other five exported products (i.e. flower, leather, hide & skin, fruit & vegetable, and spices); and ***Post*** is 1 after 2008 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E. Alternative definition of the treatment year

The Ethiopia Commodities Exchange was established in April 2008 and launched its operation by trading wheat, maize and beans. However, the world food price crisis that affected Ethiopia's grain market has led the ECX to introduce coffee trade into the exchange.[17] Hence, we address this concern by re-defining the treatment year as 2009 instead of 2008 and assess the impact of the ECX. Table 6.7 shows the triple-difference results when we assume 2009 as a beginning of the treatment year. The estimated coefficients in Columns (1)-(3) show that the ECX has a positive and statistically significant effect on coffee export. Compared to the baseline results (when 2008 is defined as the treatment year), the coefficients of the triple interaction term in Table 6.7 only vary slightly. Thus, whether we use 2008 or 2009 as the treatment year will not affect our conclusion about the statistical significance and impact of the ECX.

Table 6.7: The Impact of ECX on Coffee Export: an Alternative Treatment Year

	(1)	(2)	(3)
Treatment × ECX × Post2009	0.543***	0.543***	0.543***
	(0.048)	(0.048)	(0.048)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	No	Yes	Yes
Importer × Year	No	No	Yes
Observations	3564	3564	3564
Pseudo R^2	0.079	0.720	0.771

Note: ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other five exported products (i.e. flower, fruit & vegetable, spices, leather, and hide & skin); and ***Post*2009** is 1 after 2009 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.6 Further Analysis

6.6.1 Does the ECX Matters for the Export Extensive Margins?

The previous results primarily focus on the effect of the ECX on the intensive margin (i.e. volume) of coffee exports. However, the establishment of the ECX may also

[17] After a serous of intensive discussions with the government and other stake holders, in July 2008 a law was passed to trade and export coffee through ECX.

increase the number of destinations, the extensive margin, to which coffee is exported. In this section, we examine the effect of the ECX on the extensive margin of coffee exports. Following Cheong et al. (2017), we re-estimate Eq. (6.1) using the PPML estimator, where the dependent variable is an indicator variable that equals to 1 if positive trade flows occur to a certain product-destination-year and zero otherwise.

Table 6.8: The Effect of ECX on Coffee Export: Extensive Margin

	(1)	(2)	(3)
Treatment × ECX × Post	0.095**	0.095**	0.095**
	(0.039)	(0.039)	(0.039)
Fixed Effects			
Exporter × Year	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes
Exporter × Importer	No	Yes	Yes
Importer × Year	No	No	Yes
Observations	3564	3564	3564
Pseudo R^2	0.231	0.319	0.345

Note: Our dependent variable is an indicator variable that equals to 1 if positive trade flows occur to a certain product-destination-year and zero otherwise. ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***ECX*** is 1 for coffee exports and zero for the other five exported products (i.e. flower, fruit & vegetable, spices, leather, and hide & skin); and ***Post*** is 1 after 2008 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.8 reports the DDD results on how ECX affects the extensive margin of coffee exports. As the coefficients in Columns (1) to (3) show, regardless of the fixed effects used in the gravity model equation, the introduction of coffee in the Ethiopian agricultural exchange system increases the probability of coffee exports to new destinations by about 10%. The estimated coefficients are also statistically significant at least at the 5% level. This suggests that besides the intensive margin, a commodity exchange could also increase the extensive margins of the commodity trade.

6.6.2 ECX and the Exports of Non-ECX Commodities

Our baseline triple-differenced estimate may overestimate the impact of the ECX on coffee exports if the exports of non-ECX commodities (the the "control") are negatively affected by the ECX. For example, if the ECX leads coffee production more profitable, farmers of other agricultural commodities may switch to coffee production. As such, we examine whether the ECX has such spillover effects on exports of non-ECX commodities in Ethiopia. In carrying out this analysis, we use the following regression specification:

$$Export_{ijkt} = exp[\beta_1 Treat_i \times Product_k \times Post_t + \mu_{it} + \mu_{ik} + \mu_{kt} + \mu_{ij} + \mu_{jt}]\varepsilon_{ijkt} \tag{6.2}$$

where $Export_{ijkt}$ indicates the exports of non-ECX product k (i.e. flower, fruit & vegetable, spices and hide & skin) from country i to country j at time t. μ_{ij}, μ_{it}, μ_{ik}, μ_{kt}, and μ_{jt} represent the importer-exporter, exporter-year, exporter-product, product-year and importer-year fixed effects respectively. Our coefficient of interest in this DDD model is β_1. If ECX does not have any spillover effects, β_4 will be statistically insignificant.

Table 6.9: The Effect of the ECX on the Exports of non-ECX Commodities

	(1)	(2)	(3)	(4)
	Flower export		Fruit & Veg.	
Treatment ×Product× Post	-0.102	-0.102	-0.075	-0.075
	(0.073)	(0.073)	(0.092)	(0.092)
Fixed Effects				
Exporter × Year	Yes	Yes	Yes	Yes
Exporter × Product	Yes	Yes	Yes	Yes
Product × Year	Yes	Yes	Yes	Yes
Exporter × Importer	No	Yes	No	Yes
Importer × Year	No	Yes	No	Yes
Observations	2970	2970	2970	2970
Pseudo R^2	0.062	0.836	0.062	0.836

Note: ***Treatment*** is an indicator variable that equals 1 for Ethiopia's exported products and zero for Kenya's exported products; ***Product*** is 1 for Flower exports (Column (1) and (2)) or for fruit and vegetable exports (Column (3) and (4)) and zero for the other four non-ECX exported products (i.e. spices, leather, and hide & skin, flower or fruit & vegetable); and ***Post*2008** is 1 after 2008 and zero otherwise. Poison pseudo-maximum likelihood (PPML) estimator is employed to estimate Eq. (6.1). Exporter-Product clustered robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table (6.9) presents estimates of Eq. (6.2). The coefficient of interest (*Treatment* × *Product* ×*Post*) is statistically insignificant, suggesting that ECX does not have effect on the exports of non-ECX commodities (flower and fruit & vegetables). Thus, there is evidence that the ECX only affects coffee exports, and that the estimated effect of the ECX on coffee exports reported in the baseline is not accentuated by the effect of the ECX on non-ECX goods (as there is no evidence that such an effect exists).

6.7 Conclusion

The establishment of a agricultural commodities exchange in developing countries is often justified by arguments that it would motivate farmers to produce more and eventually to export. However, such arguments are mainly based on anecdotes, not empirical evidence. In this paper, we look at the issue of whether developing countries would benefit from having a commodity exchange. To do so, we study the effects of ECX on coffee exports in Ethiopia. Using a triple-differencing approach, we find that the establishment of the ECX has led to an increase in Ethiopia's coffee exports by about 84%. To put things into perspective, the impact of the ECX on exports is twice the impact of joining regional trade agreements (Magee, 2008) or trade concession policies such as AGOA (Frazer and Van Biesebroeck, 2010) and temporary removal of tariff following a natural disaster (Cheong et al., 2017) on trade. Therefore, a commodity exchange is worth considering for developing countries with a large agricultural sector, as the case of ECX suggests that the benefits of having a commodity exchange could be substantial.

References

Andersson, C., M. Bezabih, and A. Mannberg (2017). The Ethiopian Commodity Exchange and spatial price dispersion. *Food Policy 66*, 1–11.

Byerlee, D., A. De Janvry, and E. Sadoulet (2009). Agriculture for development: Toward a new paradigm. *Annual Review of Economics 1*(1), 15–31.

Cheong, J., D. W. Kwak, and H. Yuan (2017). Trade to aid: EU's temporary tariff waivers for flood-hit Pakistan. *Journal of Development Economics 125*, 70–88.

Craparo, A., K. Steppe, P. Van Asten, P. Läderach, L. Jassogne, and S. Grab (2017). Application of thermography for monitoring stomatal conductance of coffea arabica under different shading systems. *Science of The Total Environment 609*, 755–763.

Ferreira, K. J., J. Goh, and E. Valavi (2017). Intermediation in the supply of agricultural products in developing economies.

Frazer, G. and J. Van Biesebroeck (2010). Trade growth under the African growth and opportunity act. *The Review of Economics and Statistics 92*(1), 128–144.

Gabre-Madhin, E. (2012). *A market for Abdu: Creating a commodity exchange in Ethiopia*. Intl Food Policy Res Inst.

Gabre-Madhin, E. and I. Goggin (2006). Does Ethiopia need a commodity exchange? an integrated approach to market development. In *Ethiopian Strategy Support Program 2006 Policy Conference, Addis Ababa*.

Gabre-Madhin, E. Z. (2001). Of markets and middlemen: Transforming agricultural markets in Ethiopia. *International Food Policy Research Institute*.

Gabre-Madhin, E. Z. and I. Goggin (2005). Does Ethiopia need a commodity exchange? an integrated approach to market development. *Addis Ababa: Ethiopian Development Research Institute, Working Paper Series 4*.

Gemech, F. and J. Struthers (2007). Coffee price volatility in ethiopia: effects of market reform programmes. *Journal of International Development 19*(8), 1131–1142.

Ghosh, S. and S. Yamarik (2004). Are regional trading arrangements trade creating?: An application of extreme bounds analysis. *Journal of International Economics 63*(2), 369–395.

Gollin, D. (2010). Agricultural productivity and economic growth. *Handbook of agricultural economics 4*, 3825–3866.

Goyal, A. (2010). Information, direct access to farmers, and rural market performance in central India. *American Economic Journal: Applied Economics 2*(3), 22–45.

Haveman, J. and D. Hummels (1998). Trade creation and trade diversion: New empirical results. *Journal of Transnational Management Development 3*(2), 47–72.

Islam, N. (2016). *Agricultural policy in developing countries.* Springer.

Magee, C. S. (2008). New measures of trade creation and trade diversion. *Journal of International Economics 75*(2), 349–362.

Minten, B., S. Tamru, T. Kuma, and Y. Nyarko (2014). *Structure and performance of Ethiopia s coffee export sector*, Volume 66. Intl Food Policy Res Inst.

Moat, J., J. Williams, S. Baena, T. Wilkinson, T. W. Gole, Z. K. Challa, S. Demissew, and A. P. Davis (2017). Resilience potential of the Ethiopian coffee sector under climate change. *Nature Plants 3*(7), nplants201781.

Mutenyo, J. (2011). Driving Africas growth through expanding exports. *FORESIGHT AFRICA*, 28.

Petit, N. (2007). Ethiopia's coffee sector: A bitter or better future? *Journal of Agrarian Change 7*(2), 225–263.

Reardon, T. and C. P. Timmer (2007). Transformation of markets for agricultural output in developing countries since 1950: How has thinking changed? *Handbook of agricultural economics 3*, 2807–2855.

Silva, J. S. and S. Tenreyro (2006). The log of gravity. *The Review of Economics and statistics 88*(4), 641–658.

Silva, J. S. and S. Tenreyro (2010). Currency unions in prospect and retrospect. *Annual Review of Economics 2*(1), 51–74.

Sitko, N. J. and T. Jayne (2012). Why are African commodity exchanges languishing? a case study of the Zambian agricultural commodity exchange. *Food Policy 37*(3), 275–282.

Tiffin, R. and X. Irz (2006). Is agriculture the engine of growth? *Agricultural Economics 35*(1), 79–89.

UNCTAD (2009). *Development Impacts of Commodity Exchanges in Emerging Markets*. UNCTAD/DITC/Com/2009/9, Geneva and New York, UNCTAD.

Van der Mheen-Sluijer, J. (2010). Ethiopian commodity exchange and contract farming arrangements: Complementing institutions. Technical report, Wageningen UR.

World Bank (2008). *World Development Report 2008 : Agriculture for Development*. Washington, DC: The World Bank.

Appendix A: List of Trading Partners

Table A1: List of Trading Partners of Ethiopia and Kenya in the Sample

Austria	Belgium	Brazil	Bulgaria
Canada	China	Egypt Arab Rep.	France
Germany	Greece	India	Iran Islamic Rep.
Israel	Italy	Japan	Korea Rep.
Kuwait	Malaysia	Morocco	Netherlands
Pakistan	Romania	Russian Federation	Saudi Arabia
South Africa	Sweden	Switzerland	Thailand
Turkey	Ukraine	United Arab Emirates	United Kingdom
United States			

Note: We consider the exports of Ethiopia and Kenya for their 33 common trading partners. The sample period extends from 2003-2011.

Chapter 7

Barriers to the Diffusion of Technology Across Countries: Assessing the Impact of Genetic Distance on Firm Productivity

Dessie Tarko Ambaw[a] Firmin Doko Tchatoka[a]

Habtamu Tesfaye Edjigu [a] Nicholas Sim[a,b]

[a]*School of Economics, The University of Adelaide*

[b]*School of Business, The Singapore University of Social Sciences*

Statement of Authorship

Title of Paper	Barriers to the diffusion of technology across countries: Assessing the impact of genetic distance on firm productivity
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
Publication Details	The paper is written in publication style for submission to a journal.

Principal Author

Name of Principal Author (Candidate)	Dessie Tarko Ambaw		
Contribution to the Paper	Contributed to planning the article and the methodology, conducted the literature review, collected and analysed data, interpreted the results, and wrote part of the manuscript.		
Overall percentage (%)	35%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the co-author of this paper.		
Signature		Date	06/09/2018

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Firmin Doko Tchatoka		
Contribution to the Paper	Contributed to the planning of the article, supervised the development of the work, helped in the interpretation of the results, wrote part of the manuscript and acted as the corresponding author.		
Signature **APPROVED FDT**	Firmin Doko Tchatoka	Date	06/09/2018

Name of Co-Author	Nicholas Sim		
Contribution to the Paper	Contributed to the planning of the article and supervised the development of the work.		
Signature		Date	06/09/2018

Name of Co-Author	Habtamu Tesfaye Edjigu		
Contribution to the Paper	Contributed to planning the article and the methodology, conducted the literature review, collected and analysed data, interpreted the results, and wrote part of the manuscript.		
Signature		Date	06/09/2018

Abstract

Recent studies show that genealogically distant populations tend to differ more in a variety of characteristics transmitted intergenerationally, such as language, appearance, norms, values, customs, beliefs, and habits. Differences in these traits between countries and the world technology frontier, the US, can deter the exchange of ideas and reduce opportunities for learning, adoption of technologies, and innovations. Most of these studies, however, have often focused on country-level data and little is known at a micro-level analysis. In particular, whether genetic distance from the world technology frontier influences firm productivity in laggard countries or not is yet to be established. Building on earlier study by Comin and Hobijn (2010), we propose a theoretical framework highlighting the mechanism through which genetic distance from the world leader acts as a barrier to technology adoption in laggard countries, thus influencing negatively firms' productivity in those countries. There are some challenges in testing this theory empirically. First, the treatment variable (genetic distance) is measured at country-level while the outcome variable (firm productivity) is available at firm-level, which renders the standard panel data method useless in identifying the causal effect since the treatment is dropped out after a within-type transformation. Second, there is a substantial heterogeneity across the distribution of firms' productivity so that a mean-type regression analysis such as the two-stage least squares method is not appropriate. Using a novel method on quantile treatment models with group-level unobservables recently proposed by Chetverikov et al. (2016), we show that the impact of genetic distance on firm productivity is consistently negative and *near inverted U-shaped* across the distribution of firms' productivity. Clearly, firms operating in a country genealogically far from the technology leader tend on average to have lower level of productivity but it is often the case that two countries, one with a very low technology adoption and the other with a moderate or relatively high technology adoption can be impacted identically by the same shock on current genetic distance. This may justify why some countries that appear closer to the US have not benefited from technology adoption compared with their peers that are genealogically far from the US, or vis-versa.

Key Words: Genetic Distance; Barriers; Technology Diffusion; Firm Productivity; Quantile Treatment Models.

JEL Codes: C21; C26; O12; O14.

7.1 Introduction

Many empirical studies document substantial and persistent measured productivity differences across countries— e.g., see Hsieh and Klenow (2010) and the review by Syverson (2011). Such differences are also observed across firms within a country, even at a narrowly defined industry code (e.g., four-digit SIC); Syverson (2004). Studies aiming to explain these differences often focus on the aggregate productivity growth— the source of almost all per capita income differences across countries into various micro-components, with the intent of better understanding the sources of such growth (Hall and Jones, 1999; Foster et al., 2001; Hsieh and Klenow, 2009, 2010). It is well known that various factors– such as geography, luck, institutions, culture, and policies– can explain income differences across countries through their direct influence on human/physical capital and total factor productivity (TFP); see Hsieh and Klenow (2010). Most of these theories have been assessed empirically with success (Spolaore and Wacziarg, 2009; Bove and Gokmen, 2017; Spolaore and Wacziarg, 2016; Jäggi et al., 2018) with country-level data. However, we know little on why do firms differ so much in productivity across countries.

Earlier studies that addressed differences in productivity across countries includes Hsieh and Klenow (2010), Bartelsman et al. (2013), Restuccia and Rogerson (2008), Hsieh and Klenow (2009) and Midrigan and Xu (2014). For example, Hsieh and Klenow (2010) discuss why total factor productivity (TFP) varies across countries, highlighting misallocation of inputs across firms and industries as a key determinant. In this paper, we look at a different chain of causality that may explain differences in firms' productivity across countries. Spolaore and Wacziarg (2009) shows that genetic distance can capture cultural traits transmitted intergenerationally over the long run within populations, thus acting as a prominent source of large and persistent variations in income across countries. Following this idea and earlier study by Comin and Hobijn (2010), we proposes a theoretical framework highlighting the mechanism through which genetic distance from the world leader, the United States, acts as a barrier to technology adoption in laggard countries, thus influencing negatively the TFP of firms in those countries.

There are some challenges in testing this theory empirically. First, the treatment variable (genetic distance) is measured at country-level while the outcome variable (firm productivity) is available at firm-level, which makes the standard panel data method useless in identifying the causal effect since the treatment variable will be dropped out after a within-type transformation. Second, there is a substantial heterogeneity across the distribution of firm productivity, hence a mean-type regression analysis is not appropriate, i.e., a distributional method, such as a quantile regression analysis, is warranted. Third, due to the presence of group-level unobservables (country fixed effects) in the model, a standard quantile regression such as in Koenker and Bassett Jr (1978) will yield inconsistent estimates, thus is also not appropriate in dealing with this type of problems.

Using a novel method on quantile treatment models with group-level unobservables recently proposed by Chetverikov et al. (2016) that accommodates the above problems, along with more than 32,000 firms from 94 countries, we show that the impact of genetic distance on firm productivity is consistently negative and *near inverted U-shaped* across the distribution of firms' total factor productivity (TFP). This means that the relationship between genetic distance and TFP is not monotonically decreasing. Indeed, although firms operating in a country genealogically far from the technology leader (the US) tend to have lower level of productivity, it is also the case that a country with a very low technology adoption (i.e., a very low TFP) and that with a moderate or relatively high technology adoption can be impacted identically by the same shock on current genetic distance. This may justify why some countries that appear genealogically closer to the US have not benefited from technology adoption compared with their peers that are far from the US, or vice versa. We provide several robustness checks that show that the near inverted U-shape property of the relationship between genetic distance and the distribution of firms' TFP is: (i) robust to alternative measures of productivity and genetic distance; (ii) robust to the inclusion of institutional quality and trade openness in the model; (iii) robust to the exclusion of European countries whose genetic data are likely measured with less error than non-European countries.

Moreover, we discuss a plausible chain of causality that my explain differences in firms' TFP across countries. Indeed, we document that current genetic distance is negatively correlated with technology adoption in the 1500AD, which in turns is strongly positively associated with current median firms' TFP across countries. As such, one may expect current genetic distance to have a negative impact on the distribution (at least the median) of firms' TFP, thus corroborating the main findings of our study. It is nonetheless important to note that the latter analysis is only based on correlations, so more investigations are required to clarify if genetic distance influences firms' productivity through its impact on the technology adoption in the 1500AD. We leave these investigations for future research.

Our study contributes to the emerging empirical literature on the impact of genetic distance on technology diffusion.[1] For example, Spolaore and Wacziarg (2009) show that genetic distance is a key determinant of differences in income across countries, and their result is robust to the inclusion of covariates such as geographical distance, climatic differences, transportation costs, and measures of historical, linguistic, and religious distance. Bove and Gokmen (2017) show that the negative impact of genetic distance on income across countries is stable over time, while Proto and Oswald (2017) establish that some nations may have a genetic advantage in well-being– e.g., the closer is a nation to the genetic makeup of Denmark the happier this nation is. Similarly, Ang and Kumar (2014) investigate the impact of genetic distance from the world technology frontier on financial development. They find that genetic distance negatively affects financial development through its influence on countries ability to adopt innovations from the frontier technology. Although all these studies have some similarity with ours, there are two fundamental differences. First, our study examines the impact of a group-level treatment (genetic distance, that is measures at country-level) on a micro-level outcome (firms' TFP, that measures at firm-level), while theirs focus on a group-level analysis as both their treatment (genetic distance) and the outcome (income/financial development) variables are measured at country-level. Second, while their studies focus on a

[1]See Giuliano et al. (2006), Spolaore and Wacziarg (2009), Guiso et al. (2009),Ang and Kumar (2014), Bove and Gokmen (2017), Ashraf and Galor (2013b) and Ashraf and Galor (2013a).

mean-type regression analysis, we show that a distributional approach is warranted to capture heterogeneity across the distribution of the outcome variable. As such, applying a mean-type regression approach, such as the 2SLS method, often yields an inconsistent estimate of the treatment impact on the outcome variable.

The rest of the paper is organized as follows. Section 7.2 presents the theoretical framework that leads to a testable empirical econometric specification. Section 7.3 presents the empirical specification and describes the estimation strategy. Section 7.4 provides a brief description of the data, including the data sources and the main variables used in the paper. Sections 7.5 presents the baseline results, while Section 7.7 provides some robustness checks. Section 7.8 introduces a brief mechanism that may justify the main results of the paper, while Section 7.9 contains the concluding remarks.

7.2 Theoretical Framework

A theoretical model describing the mechanism through which *genetic distance* from the frontier country can endogenously affects *technology adoption* in laggard countries (thus impacting on firms' productivity) was first developed Comin and Hobijn (2010). In this section, we show how this theoretical framework can be adapted to a micro level analysis. In particular, we demonstrate how *genetic distance* can influence firms' total factor productivity (TFP), and we test the theory with an econometric specification.

Following Comin and Hobijn (2010), we consider a three sectors model: the households, the world technology frontier, and the firms. We assume there are identical **households** in the economy with unit mass. Each household supplies inelastically a unit of labor, receives wage (w), and saves in bonds that are available in the domestic market with zero net supply. The representatives household maximizes his life time utility subject to the budget constraint and the no-Ponzi scheme condition on bonds. **The technology frontier country** is characterized by a set of technologies and vintages specific to each technology at time t. At each instant t a new technology (τ) exogenously appears. Denoting a technology by the time it was invented, the range of technologies invented by the frontier country are given by $(-\infty, t]$. For each existing technology, a new and more productive vintage appears in the world frontier at every t. We denote the vintage of technology τ by V_τ. Vintages are indexed by the time in which they appear. Hence, the set of existing vintages of technology τ available at time t is $[\tau,\ t]$. The productivity of a technology has two components: $Z(\tau, V_\tau)$ and a_τ. The component $Z(\tau, V_\tau)$ is common across countries and is purely determined by technological attributes, i.e.

$$Z(\tau, V_\tau) = e^{(\chi+\gamma)\tau+\gamma(V_\tau-\tau)} = e^{(\chi\tau+\gamma V_\tau)} \tag{7.1}$$

where $(\chi+\gamma)\tau$ is the productivity level associated with the first vintage of technology τ and $\gamma(V_\tau - \tau)$ represents the productivity level associated with the introduction of new vintages. The second component, a_τ, is the country specific productivity term that is described in (7.2) below.

Identical **firms** operate competitively in each country. They adopt a new technology τ from the frontier countries, combine it with labor and intermediate goods to produce output. We assume countries that are adopting a technology τ are below the world technology frontier country. If D_τ denotes the *adoption lag* that reflects the time lag between when the best vintage in use was invested and when it was invented for production in the economy, then the vintage of technology τ is defined as $V_\tau = [\tau, t - D_\tau]$ and represents the set of technology-τ vintages available in the economy. We also assume that new vintages (τ, V), where $V \equiv V_\tau$ hereinafter, are used in production through new intermediate goods that embody them. Intermediate goods $X_{\tau,V}$ are combined with labor $L_{\tau,V}$ to produce output $Y_{\tau,V}$ associated with a given vintage. The form of the production function for $Y_{\tau,V}$ is given by:

$$Y_{\tau,V} = a_\tau Z(\tau, V) X_{\tau,V}^{\alpha} L_{\tau,V}^{1-\alpha}. \tag{7.2}$$

In (7.2), a_τ represents the factors that reduce the effectiveness of a technology in a country. Comin and Mestieri (2014) designate it as barriers to the diffusion of technology. a_τ also determines the *long-run penetration rate* of technology in a given country, thus is usually referred to as the **intensive margin** of technology adoption.

The representative firm combines the outputs associated with the different vintages of the same technology to produce the sectoral output, Y_τ, given by

$$Y_\tau = \Big(\int_{\tau}^{t-D_\tau} Y_{\tau,V}^{\frac{1}{\mu}} dV \Big)^{\mu} \quad \text{for some} \;\; \mu > 1. \tag{7.3}$$

The final output is thus obtained by aggregating sectoral outputs Y_τ:

$$Y = \Big(\int_{-\infty}^{\overline{\tau}} Y_\tau^{\frac{1}{\theta}} d\tau \Big)^{\theta} \quad \text{for some} \;\; \theta > 1, \tag{7.4}$$

where $\overline{\tau}$ denotes the most advanced technology adopted in the economy.

As shown by Comin and Hobijn (2010), the '**factor demand**' and '**final output** can be derived straightforwardly. More precisely, taking the price of the final output as the numeraire, both he demand for an output produced with a given technology and that of a particular technology vintage are given by:

$$
\begin{aligned}
Y_\tau &= Y P_\tau^{-\frac{\theta}{\theta-1}} && (7.5)\\
Y_{\tau,V} &= Y_\tau \Big(\frac{P_{\tau,V}}{P_\tau}\Big)^{-\frac{\mu}{\mu-1}}, && (7.6)
\end{aligned}
$$

where P_τ is the price of sector τ output and $P_{\tau,V}$ refers to the price of the (τ, V) intermediate good. Equation (7.5) indicates that both the national income (Y) and the price of the technology (P_τ) affect the demand of output produced with a given technology τ. Due to the homotheticity of the production function, the income elasticity of technology τ output is one. Thus under perfect competition, the demand for labor and intermediate goods at the vintage level are then given by:

$$(1-\alpha)\frac{P_{\tau,V} Y_{\tau,V}}{L_{\tau,V}} = w, \tag{7.7}$$

$$\alpha\frac{P_{\tau,V} Y_{\tau,V}}{X_{\tau,V}} = 1. \tag{7.8}$$

Combining (7.2) and (7.7)-(7.8) gives:

$$P_{\tau,V} = \frac{w^{1-\alpha}}{Z(\tau,V)a_\tau}(1-\alpha)^{-(1-\alpha)}\alpha^{-\alpha}. \tag{7.9}$$

From (7.3), we can thus express the production function of total output produced with technology τ as:

$$Y_\tau = Z_\tau L_\tau^{1-\alpha} X_\tau^\alpha, \tag{7.10}$$

where $L_\tau = \int_\tau^{t-D_\tau} L_{\tau,V} dV$ is the total amount of labor employed in sector τ, $X_\tau = \int_\tau^{t-D_\tau} X_{\tau,V} dV$ is the productivity level associated with technology τ, and Z_τ denotes the total amount of intermediate goods in sector τ, i.e.

$$
\begin{aligned}
Z_\tau &= \left(\int_\tau^{max(t-D_\tau,\tau)} Z(\tau,V)^{\frac{1}{\mu-1}} dV\right)^{\mu-1}\\
&= \left(\frac{\mu-1}{\gamma}\right)^{\mu-1} \underbrace{a_\tau}_{\text{Intensive margin}} \underbrace{e^{(\chi\tau+\gamma max\{t-D_\tau,\tau\})}}_{\text{Embodiment effect}} \underbrace{\left(1-e^{\frac{-\gamma}{\mu-1}(max\{t-D_\tau,\tau\}-\tau)}\right)^{\mu-1}}_{\text{Variety effect}}.
\end{aligned}
\tag{7.11}
$$

Equation (7.11) indicates clearly that the productivity of technology τ is determined by three factors: the intensive margin (a_τ), the embodiment effect (which shows the productivity of the best vintage), and the variety effect (which represents the productivity gains from using more vintages). As such, the adoption lag D_τ has two effects on Z_τ. First, the shorter D_τ the more productive are the vintages used. Second, a shorter D_τ implies that more varieties are used, which in turns leads to higher productivity.

From (7.9), we can express the price index of technology τ output's as:

$$P_\tau = \left(\int_\tau^{t-D_\tau} P_{\tau,V}^{-\frac{1}{\mu-1}} dV\right)^{-(\mu-1)} = \frac{w^{1-\alpha}}{Z_\tau}(1-\alpha)^{-(1-\alpha)}\alpha^{-\alpha}. \tag{7.12}$$

Following Comin and Hobijn (2010), the process that governs the **diffusion of technology** in this model is given by:

$$y_\tau - y = \frac{\theta}{\theta-1}[z_\tau - (1-\alpha)(y-l)], \tag{7.13}$$

where y_τ is the log of sectoral output produced with technology τ, y is the log of final (aggregate) output, hence $y_\tau - y$ is the log of the share of sectoral output with technology τ in the total output, θ is the elasticity of substitution, z_τ is the log of productivity associated with technology τ, $1-\alpha$ is the share of labor in the production of y_τ, l is the log of the total amount of labor employed in the production of Y, and $(y-l)$ represents the log of per capita output.

From (7.11), we can write z_τ when $\max\{t-D_\tau, \tau\} = t - D_\tau$ as:

$$\begin{aligned} z_\tau \;&=\; (\mu-1)ln(\frac{\mu-1}{\gamma}) + ln(\alpha_\tau) + \chi\tau + \gamma(t-D_\tau) + \\ &\quad + \;(\mu-1)ln\big(1-e^{-\frac{\gamma}{\mu-1}(t-D_\tau-\tau)}\big). \end{aligned} \tag{7.14}$$

Applying a double Taylor expansions to (7.14) as in Comin and Hobijn (2010) yields:[2]

$$z_\tau = ln(\alpha_\tau) + (\chi+\gamma)\tau + (\mu-1)ln(t-\tau-D_\tau) + \frac{\gamma}{2}(t-\tau-D_\tau) + R(t-D_\tau-\tau;\gamma,\mu), \tag{7.15}$$

[2]Where we first take a Taylor expansion of order 2 of $1-e^{-\frac{\gamma}{\mu-1}(t-D_\tau-\tau)}$ around the starting adoption date, and then apply the log operator to the result, and take again a Taylor expansion of order 1 of the latter result.

where $R(\cdot)$ is the accumulated error resulting from the two expansions and is a function of $t-\tau-D_\tau$ and the parameters γ and μ. The log intensive margin, $ln(\alpha_\tau)$, appearing on the RHS of (7.15) incorporates all the sets of barriers for the adoption of technology τ by the country, $(\chi+\gamma)\tau$ is the associated productivity level, μ is the elasticity of substitution parameter in the sectoral output production function, while D_τ is the age of the best vintage available for production in the country for technology τ.

By substituting (7.15) into (7.13), we can write $y_\tau - y$ as:

$$y_\tau - y = \delta_\tau + \gamma_1 t + \gamma_2 ln(t-\tau-D_\tau) + \delta_1 ln(\alpha_\tau) + \delta_2(y-l) + R(t-D_\tau-\tau;\gamma,\mu,\theta), \quad (7.16)$$

where $\delta_\tau = \frac{\theta}{\theta-1}\left[(\chi+\frac{\gamma}{2})\tau - \frac{\gamma}{2}D_\tau\right]$, $\gamma_1 = \frac{\theta}{(\theta-1)}\frac{\gamma}{2}$, $\gamma_2 = \frac{\theta}{\theta-1}(\mu-1)$, $\delta_1 = \frac{\theta}{\theta-1}$, $\delta_2 = -\frac{\theta}{\theta-1}(1-\alpha)$, and $R(t-D_\tau-\tau;\gamma,\mu,\theta) = \frac{\theta}{\theta-1}R(t-D_\tau-\tau;\gamma,\mu)$. Clearly, (7.16) is the linear projection of $y_\tau - y$ on a constant, time trends t and $ln(t-\tau-D_\tau)$, the log intensive margin a_τ, and the log of per capita output, where $R(t-D_\tau-\tau;\gamma,\mu,\theta)$ can be viewed as the error associated with this projection. As such, the long-run barriers to the diffusion of technology to a country are captured by the intensive margin α_τ [similar to Comin and Ferrer (2013) and Comin and Mestieri (2014)]. In particular, Comin and Mestieri (2014) highlights that the factors that determined the intensive margin (α_τ) for a given country are: *genetic distance* from the frontier country, human capital, geographical factors (such as landlockedness, distance from the technology frontier, tropical land area), openness to trade, institutional factors and other cultural factors. Therefore, we can specify a linear model for the intensive margin (in natural log) as:

$$ln(\alpha_\tau) = \phi_0 + GD\phi_1 + \boldsymbol{X}\phi_2 + v_\tau, \quad (7.17)$$

where GD is the measure of genetic distance from the technology frontier, $\boldsymbol{X}$ includes other control variables (landlockedness, absolute latitude, tropical land area, legal origin, language distance, and religion distance), ϕ_0 is the intercept, ϕ_1 is the coefficient on genetic distance, ϕ_2 denotes a parameter vector on $\boldsymbol{X}$, and v_τ is an error term. By substituting (7.17) into (7.16), we obtain the specification

$$y_\tau - y = \beta_\tau + \gamma_1 t + \gamma_2 ln(t - \tau - D_\tau) + GD\beta_1 + W\beta_2 + \varepsilon_\tau, \tag{7.18}$$

where $\beta_\tau = \delta_\tau + \delta_1\phi_1$, $\beta_2 = (\phi_2', \delta_2')'$, $W = [\boldsymbol{X} \vdots y - l]$, and $\varepsilon_\tau = R(t - D_\tau - \tau; \gamma, \mu, \theta) + \delta_1 v_\tau$. In this study, we investigate how a relationship such as (7.16) evolves at a micro-level (i.e., at firms level), rather than a country-level as usually done in the literature on this topic.

To enable a micro-level analysis, we look at the diffusion of total factor productivity (TFP) of firms as oppose to output in the country-level specification (7.16). In particular, our main objective is to identify the effect of *genetic distance* on firms' TFP in developing countries. We stress the fact that TFP is often regarded as a measure of technology in the economy, especially in the early versions of real business cycle (RBC) models where it is well documented that growth in TFP drives growth in the long term. The main difficulty in our analysis is that genetic distance (treatment variable of interest) is measured at country-level while TFP data are available at firm-level. This render the standard panel data method such as fixed estimation useless in identifying β_1 since the variable GD will disappear after a within-type transformation. Using recent developments on quantile treatment models with group-level unobservables, we are able to identify β_1 (the effect of genetic distance on TFP) despite the presence of grup-level unobservable confounding factors. Section 7.3 details the empirical specification as well as the estimation strategy.

7.3 Empirical Specification

To identify the effect of genetic distance on TFP, we use a quantile treatment approach when group-level unobservables are present. Section 7.3.1 presents the specification used, while issues related to model identification are discussed in Section 7.3.2. Finally, Section 7.3.3 describes briefly the measurement of firms' total productivity (TFP) by the World Bank analysis unit.

7.3.1 Model

Let $\mathcal{U}$ denote a set of quantile indices and consider the framework of IV quantile regression for grouped-level treatments (Chetverikov et al., 2016):

$$Q_{TFP_{ic}|GD_c,X_{ic},Z_c,\varepsilon_c}(u) = GD_c\beta(u) + X_{ic}'\gamma_1(u) + Z_c'\gamma_2(u) + \varepsilon_c(u) \tag{7.19}$$

$$\varepsilon_c(u) = f(u, \eta_c), \tag{7.20}$$

where $Q_{TFP_{ic}|GD_c,X_{ic},Z_c,\varepsilon_c}(u)$ is the uth conditional quantile of TFP_{ic} given $(GD_c, X_{ic}, Z_c, \varepsilon_c)$ for firm i in country c, GD_c is a measure of genetic distance of country c with respect to the global technological frontier (here the US), X_{ic} is a vector of firm-level characteristics[3] that affect the productivity of firm i in country c, Z_c is a vector of country-level control variables,[4] $\varepsilon_c \equiv \{\varepsilon_c(u) : u \in \mathcal{U}\}$ is a set of country-level unobserved random shifters which maps the unobserved country-level covariates η_c affecting TFP_{ic} but not included in Z_c through an unknown function $f(\cdot)$. There is no parametric restriction on the form of $f(u, \eta_c)$, hence any arbitrary nonlinear effects of the country-level unobserved covariates are allowed. The parameters $\beta(u)$ and $\gamma_j(u)$ $(j = 1, 2)$ are unknown: $\beta(u)$ and $\gamma_2(u)$ represent the effect of group-level covariates, while $\gamma_1(u)$ represents those of individual-level covariates. Industry specific effect is omitted from (7.19)-(7.20) because the study focuses on manufacturing firms only and the estimation of the TFP (see Section 7.3.3) assumed homogeneity in technology within each sub-sector of industries, including the manufacturing sector.[5] We assume that X_{ic} and Z_c are exogenous, i.e., $\mathbb{E}[X_{ic}\varepsilon_c(u)] = 0$ and $\mathbb{E}[Z_c\varepsilon_c(u)] = 0$, but GD_c may be endogenous due to various reasons discussed in the next subsection.

We are particularly interested in estimating $\beta(u)$, which measures the effect of genetic distance on TFP at the uth quantile. As discussed previously, most studies

[3]These include age, size and ownership types.

[4]These include GDP, per capita income, trade openness, institution, tertiary education, legal origin, language, and religion distance and geographical variables such as landlockedness, absolute latitude, tropical region, land area, distance.

[5]The World Bank classifies industries into sectors of two-digit ISIC codes, and estimates TFP of each firms by controlling for sectoral fixed effects. Due to homogeneity in the production function across firms within sub-sectors, sectoral fixed effects constitute good approximation of industries specific effects, and the latter are quite constant within each sub-sector in the classification of the World Bank.

on the topic have taken the mean regression approach which does not allow to account for heterogeneous effect of genetic distance across the distribution the TFP variable. For example, one expect the effect of genetic distance to be higher on the upper quantiles of the distribution of TFP than the lower quantiles, but the mean-type regression cannot pick up these differences. Chetverikov et al. (2016) outlined the difficulty to identify $\beta(u)$ using the traditional fixed effect panel data method. Indeed, the genetic distance variable (GD_c) is measured at country-level, hence is constant across firms in a given country. As such, a within-group transformation will eliminate it from the regression. Chetverikov et al. (2016) propose a quantile estimation method that can be applied even in the presence of country-level unobservables [i.e., $\varepsilon_c(u)$]. Before moving on to the description of this method, it is important discuss issues related to the identification of $\beta(u)$ in model (7.19)-(7.20).

7.3.2 Threat to Identification and Estimation Strategy

The presence of country-level unobservables render the use of standard quantile regression techniques, such as the methodology of Koenker and Bassett Jr (1978), inconsistent, and this is true even if the country-level treatment variable, GD_c, were exogenous. Recent studies have expanded Koenker and Bassett Jr (1978) framework to models similar to (7.19)-(7.20); see Kato et al. (2012) and Kato and Galvao (2011). However, these studies often focus on estimating $\gamma_1(u)$ (rather than $\beta(u)$) so that a within-group transformation still applies. As the focus of our study is to estimate $\beta(u)$, the techniques in Kato et al. (2012) and Kato and Galvao (2011) are not applicable and an alternative method is warranted.

Another problem is that GD_c is possibly endogenous in (7.19)-(7.20). This, along with the presence of country-level unobservables ε_c, complicate further the identification of $\beta(u)$. They are various reasons sustaining the endogeneity of GD_c in this model. First, the unobserved country specific effect (η_c) affecting firms productivity are likely to be correlated with *genetic distance* (e.g., see Spolaore and Wacziarg, 2009). Second, *genetic distance* is possibly measured with error due to migration (e.g., see Spolaore and Wacziarg, 2009; Ang and Kumar, 2014), therefore cannot be exogenous. Third, they may be a problem of reverse causality as migration could lead to a pattern of genetic distances today that is closely linked to technology adoption and productivity. To identify the causal effect of GD on TFP, it is important to account for these problems. Since we are interested only on the effect that genetic distance exert on TFP, we did not specify a full system showing all interactions between GD and TFP. Rather, we adopt the limited information approach as described in (7.19)-(7.20). In particular, we deal with the endogeneity issue by using the measure of genetic distance from the UK in 1500 relative to the English population (namely $GD^{1500}_{c,UK}$) as an instrumental variable (IV) for GD_c. We argue that $GD^{1500}_{c,UK}$ does not have a direct influence on the current TFP of laggard countries as the mass migration of the modern era started after 1500. $GD^{1500}_{c,UK}$ is also possibly a strong instrument because it likely highly correlated with the current genetic distance of laggard countries which are measured relative to the US. A failure of at least one of these two conditions constitutes a threat to identification. While the strength of $GD^{1500}_{c,UK}$ can be assessed using, for example, a weak IV test,[6] unfortunately its validity cannot be tested since the model is exactly identified (in the sense that we only have one instrument and one endogenous regressor in the specification).

Now, suppose that the orthogonality condition $\mathbb{E}[GD^{1500}_{c,UK}\varepsilon_c(u)] = 0$ is satisfied for all $u \in \mathcal{U}$, i.e., $GD^{1500}_{c,UK}$ is a valid instrument for GD at every quantile of the distribution of TFP. From Chetverikov et al. (2016), $\beta(u)$ can be consistently estimated following a two-step methodology as described below.

Step 1 : For each country c and each quantile $u \in \mathcal{U}$, estimate the uth quantile regression of TFP_{ic} on X_{ic} and Z_c using the data $\{(TFP_{ic}, X_{ic}, Z_c) : i = 1, \ldots, N_c\}$ by the classical quantile regression of Koenker and Bassett Jr (1978):

$$\widehat{\alpha}(u) \quad = \quad \arg\min_a \sum_{i=1}^{N_c} \rho_u\big(TFP_{ic} - \widetilde{Z}'_{ic}a\big), \tag{7.21}$$

where $\rho_u(x) = \big(u - \mathbb{1}[x < 0]\big)x$ for $x \in \mathbb{R}$, $\widehat{\gamma}(u) = \big[\widehat{\beta}_c(u), \widehat{\gamma}'_{1c}(u), \widehat{\gamma}'_{2c}(u)\big]'$, $\widetilde{Z}_{ic} = \big(GD_c, X'_{ic}, Z'_c\big)'$.

[6] See **?**.

Step 2 : Estimate a 2SLS regression of $\widehat{\beta}_c(u) \equiv \widehat{\beta}_c$ on GD_c using $GD^{1500}_{c,UK}$ as an instrument ($c = 1, \ldots, G$) to get an estimator $\widehat{\beta}(u)$ of $\beta(u)$, i.e.

$$\widehat{\beta}(u) \quad = \quad \left(GD' P_{GD^{1500}_{UK}} GD\right)^{-1} GD' P_{GD^{1500}_{UK}} \widehat{A}(u), \tag{7.22}$$

$GD = (GD_1, \ldots, GD_G)'$, $GD^{1500}_{UK} = (GD^{1500}_{1,UK}, \ldots, GD^{1500}_{G,UK})'$, $\widehat{A}(u) = (\widehat{\beta}_1, \ldots, \widehat{\beta}_G)'$, and for any full-columns rank matrix W, $P_W = W(W'W)^{-}W'$ is the projection matrix on the space spanned by the columns of W.

The estimator $\widehat{\beta}(u)$ in (7.22) is consistent and asymptotically normal if $G \to \infty$ and $G^{2/3} ln(N_G)/N_G \to 0$, along with other regularity conditions (Chetverikov et al., 2016, Assumptions 1–8), where $N_G = \min\limits_{c=1,\ldots,G} N_c$. It is worth noting that the number of countries in our sample is $G = 94$, which may not be very large as required for $\widehat{\beta}(u)$ to achieve consistency and asymptotic normality. However, the Monte Carlo simulations (see Chetverikov et al., 2016, Table A.I) show that $\widehat{\beta}(u)$ has an overall good properties even when $G = 25$, which is far less than 94 groups in our sample.

7.3.3 Measurement of Total Factor Productivity (TFP)

This study uses TFP data from the World Bank (WB) analysis unit, and have been estimated following a two-step methodology. First, the production function is estimated for each industry in each country. Then, firms' TFP is deduced as a Solow residual of this production function.

More specifically, consider the following Cobb-Douglas production function:

$$Y_i = A_i K_i^{\alpha_k} L_i^{\alpha_l}, \tag{7.23}$$

where Y_i is the output of firm i, L_i is labor inputs (represented by the total annual cost of labor), K_i is the capital (represented by the replacement value of machinery, vehicles, and equipment), and A_i measures the TFP of the firm.[7] Due to the lack of physical output data, the WB analysis unit employs a revenue-based estimation

[7] We have also used the estimates of TFP based on an extension of model (7.23) that includes raw material (M_i) and our main findings are quality the same with those using TFP measured from (7.23).

of the TFP, i.e., Y_i is the total annual sales of the establishment. This approach raises some econometric issues. First, input choice is likely to be correlated with the productivity of the producers. Second, there may be a selection bias as less efficient producers are more likely to exit from the sample. Syverson (2011) argues that the selection problem is not important because producers with high productivity will likely be efficient regardless of the specific way their productivity is measured.

Another problem also is that the specification (7.23) assumes perfectly competitive markets with common production technology. This assumption is restrictive, and in order to incorporate some form of heterogeneity, the WB analysis unit estimates the production function (7.23) by grouping industries in sectors of two-digit ISIC codes. The elasticities of labor and capital (a_k and a_l) are allowed to vary by income-level categorized according to the WB classification. To control for an average economy-level and time specific effects, dummy variables for each country and year are included. More specifically, the econometric model used by the WB to estimate TFP at the sectoral level is given by:

$$\begin{aligned} \ln(Y_{isc}) &= \alpha_1 \ln(K_{isc}) + \alpha_2 \ln(L_{isc}) + \alpha_3 \ln(K_{isc}) \times I_c + \alpha_4 \ln(L_{isc}) \times I_c + \nu_{isc} \\ \nu_{sci} &= \omega_c + \omega_y + \lambda_s + \zeta_{isc}, \end{aligned} \tag{7.24}$$

where $ln(Y_{isc})$, $ln(K_{isc})$, and $ln(L_{isc})$ are the natural log of output, capital, and labor respectively, of firm i in sector s and country c; I_c is a dummy variable indicating whether country c is high or low income based on the WB classification as of the year in which each survey was conducted; ω_c and ω_y captures country and year fixed effects, while λ_s is sector specific effect, and ζ_{isc} are idiosyncratic shocks. The total factor productivity (TFP_{isc}) is the Solow residual of the production function, therefore is approximated by the residual from the regression (7.24) including the fixed effect terms, i.e.

$$\widehat{TFP}_{isc} = \widehat{\omega}_c + \widehat{\omega}_y + \widehat{\lambda}_s + \widehat{\zeta}_{isc}. \tag{7.25}$$

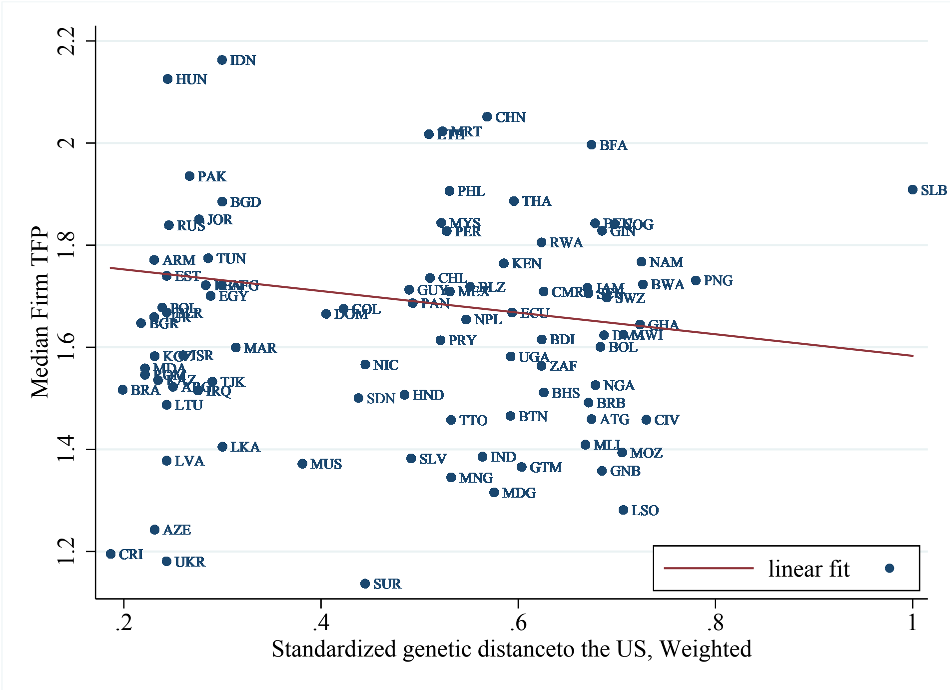
7.4 Data

The data on firms are obtained from the World Bank enterprise survey (WBES). The survey was conducted between 2006 and 2010 on more than 30,000 manufacturing firms from over 100 countries. The survey questionnaire contains identical questions for all countries and industries were stratified by size and income level. The survey provides an exhaustive information on firm-level productivity (TFP) estimates (the fraction of output that is not explained by the amount of inputs used), firms' commencement year, ownership type, sale, labor, capital and other important variables. The survey also provides a revenue-based firm-level productivity estimates (World Bank, 2017).

The macro-level variables are collected from different sources. The treatment variable (i.e., genetic distance to the world technological frontier–the US) is from Spolaore and Wacziarg (2017), and includes culture, habits, values and customs (Spolaore and Wacziarg, 2009). It is important to note this measure is based on the assumption that differences in gene distributions between populations across a range of neutral genes show the time that has passed since two populations shared common ancestors (Spolaore and Wacziarg, 2009). In this study, we view the genetic distance to the US as a measure of the extent of genetic relatedness between populations of laggard countries and the US. Following Spolaore and Wacziarg (2009), we use data on genetic distance weighted by the share of population belonging to each distinct ancestral group in each country. This variable is standardized to take values between 0 and 1, where a value of 0 shows that the two populations have identical genetics and that of 1 indicates the two populations are completely different.

Figure 7.1 plots the median level of TFP against the normalized genetic distance to the US. The scatter plots show a negative relationship between genetic distance and median TFP, thus confirming the idea that genetic distance is related to barriers to the diffusion of technology from the world frontier (here the US). While countries like Costa Rica and Brazil appear closer to the US in terms of genetic distance, Papua New Guinea and Solomon Islands are genealogically very far from the US. Some African countries like Morocco, Middle East countries like Turkey, Iran and Afghanistan, and

Figure 7.1: Standardized Genetic Distance and Median TFP of Firms



Eastern European countries like Ukraine, Russia, Lithuania, and Bulgaria also appear genealogically close to the US. The figure also illustrates some form of heterogeneity across the distribution of median TFP, meaning that a mean-type regression may under-or over-estimate the impact that genetic distance exerts on TFP. As such, our quantile regression approach is better suited to this type of analysis as it captures the heterogeneity across the distribution of TFP, as opposed to a mean-type regression analysis employed in various seminal work on the topic.

Table 7.1 provides the descriptive statistics of the main variables in the sample, this includes the first, second and third quartiles of the main firm-level characteristics and country-level variables. Three observations stand out from the table. First, the dependent variable (TFP) and the treatment variable (genetic distance) appear quite dispersed, which translates into their first, second and third quartiles being quite different, thus highlighting some form of heterogeneity of TFP. Second, the distribution of the technology adoption in the 15 century was more heterogeneous across countries than it was in the 20 century, as showed per the growth of their quartiles. Finally, the genetic to the UK in the 15 century is quite heterogeneous across the three quartiles, thus underling that the instrument GD_{UK}^{1500} exhibits some variability in the sample, which is needed for the identification of the model.

Table 7.1: Summary Statistics

Variables	Mean	Std. Dev	Min	Max	Q 0.25	Q 0.50	Q 0.75
Total factor productivity (TFP)	1.762	1.000	-2.356	5.584	1.101	1.698	2.384
Genetic distance to US, weighted	0.031	0.011	0.008	0.07	0.020	0.036	0.040
Genetic distance to UK (1500 match)	0.017	0.012	0	0.046	0.008	0.013	0.030
Genetic distance to UK, weighted	0.018	0.013	0.001	0.058	0.005	0.013	0.030
Technology adoption (1500Ad)	0.460	0.282	0	0.9	0.166	0.466	0.758
Technology adoption (2000)	0.381	0.100	0.173	0.856	0.316	0.368	0.450
Firm age	20	16	11	214	9	15	25
Export_dummy	0.104	0.306	0	1	0	0	0
Foreign_dummy	0.095	0.293	0	1	0	0	0
log(Gross domestic product)	25.492	1.880	19.820	28.713	23.774	25.737	27.015
log (Per capita income)	7.765	1.036	5.338	10.185	6.791	7.746	8.748
log (Trade openness)	4.024	0.450	3.296	5.324	3.640	3.981	4.238
Institution quality	-2.004	3.802	-14.118	9.610	-4.648	-2.180	0.170
Language distance	0.961	0.054	0.367	1	0.933	0.974	1
Geographical distance	9880	3947	2387	16465	8069	10213	13131
Religious distance	0.822	0.135	0.602	1	0.661	0.890	0.921
Legal origin	0.286	0.452	0	1	0	0	1
landlockedness	0.095	0.293	0	1	0	0	0
Tropical	0.575	0.420	0	1	0.037	0.512	1
Latitude	0.236	0.236	0	1	0.111	0.222	0.333
Africa	0.267	0.442	0	1	0	0	1

Note. Table 7.1 presents the summary statistics from the pooled sample for the main firm-level and macro-level variables. Q 0.25, Q 0.50 and Q 0.75 symbolize the 25%, 50%, and 75% quantiles, respectively.

7.5 Estimation and Interpretation of Results

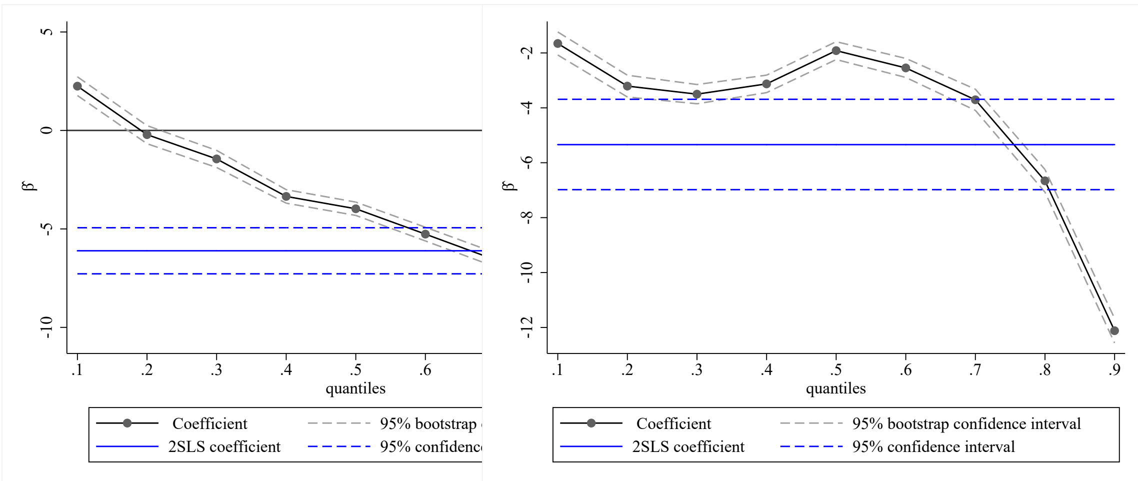
To shorten the presentation of the paper, our analysis focuses on the estimated impact of the treatment variable of interest (genetic distance measure), i.e., the quantile estimates $\widehat{\beta}(u), u \in \mathcal{U}$ from model (7.19)-(7.20). To facilitate readability and understanding our results, we use a combination of graphical representations and summary tables.

7.6 Baseline Results

Table 7.2 presents the estimated impact of genetic distance on TFP. Column (1) reports the two stage least square (2SLS) estimates obtained through a mean-regression, while columns (2)-(6) contains the 10th, 30th, 50th, 70th, and 90th quantile estimates. In *Panel A*, we do not control for micro- and macro-level covariates, while those exogenous covariates are accounted for in *Panel B*. While the robust standard errors are reported for the 2SLS estimates, the bootstrap ones are presented in all tables for the quantile estimates. Several interesting observations are of order.

First, the estimated impact of genetic distance on TFP, both at the mean and across the quantiles, is negative after controlling micro- and macro-level exogenous covariates (*Panel B*), confirming the conjecture that *genetic distance* acts as a barrier to technology adoption by firms of laggard countries from the technological frontier (i.e., the US). Second, 2SLS method tends to overestimate the magnitude of the impact of genetic distance on TFP from the lower up to the middle upper part of the distribution of TFP, while the method overwhelmingly underestimates this impact at the upper top of the distribution of TFP. This pattern is illustrated clearly in Figure 7.2(b) where a significant range of the quantile estimates $\widehat{\beta}(u)$ are consistently above the 2SLS estimates before falling below at the very top of the distribution of TFP. These results underline a significant heterogeneous effect of genetic distance across the distribution of TFP, implying that a mean-type regression analysis– such as the 2SLS method– could be misleading. For example, while the 2SLS estimate (*Panel B*) indicates that a 1 percentage point increase in genetic distance from the technology frontier leads to a 5.34% average decline in firm productivity of laggard countries, this effect is roughly 1.65% for the countries situated at the 10th quantile of TFP, 3.50% for those at the 30th quantile, 1.92% for those at the 50th quantile, 3.71% for those at the 70th quantile, and 12.12% for those at the 90th quantile. Third, an appealing and certainly interesting finding is that the impact of genetic distance across the distribution of TFP is a near inverted U-shape, meaning that the relationship between genetic distance and TFP is not monotonically decreasing as postulates the 2SLS estimation. Indeed, it clearly from Figure 7.2(b) and others that a country with a very low technology adoption (ranked from 0 up to 30th quantile) and a country with moderate technology adoption (ranked in 30th–50th quantile) or relatively high technology adoption (ranked in 50th–70th) can be impacted identically by the same shock on current genetic distance. This may indicate why some countries that appear closer to the US (the World technology frontier) have not benefited from technology adoption compared with their peers that are genealogically relatively far from the US, or vis-versa.

Figure 7.2: The Effect of the Genetic Distance on Firm Productivity



(a) Without exogenous covariates

(b) With micro and macro covariates

Table 7.2: The Effect of Genetic Distance from US on Firm Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
		Quantile				
Panel A: Without controls	2SLS	0.10	0.30	0.50	0.70	0.90
F_{ST} gen. dist. to	-6.11***	2.25***	-1.45***	-3.97***	-6.56***	-10.37***
the US, weighted	(0.5966)	(0.2426)	(0.2213)	(0.1728)	(0.1818)	(0.2114)
Individual Controls	No	No	No	No	No	No
Macroeconomic Controls	No	No	No	No	No	No
Country FE	No	Yes	Yes	Yes	Yes	Yes
Number of countries	94	94	94	94	94	94
Number of firms	32,038	32,276	32,276	32,276	32,276	32,276
Panel B: With all controls						
F_{ST} gen. dist. to	-5.3394***	-1.65***	-3.50***	-1.92***	-3.71***	-12.12***
the US, weighted	(0.8409)	(0.2141)	(0.1788)	(0.1665)	(0.1965)	(0.2271)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	94	94	94	94	94	94
Number of firms	31,212	31,500	31,500	31,500	31,500	31,500

Note. The micro variables include age, export dummy, firm ownership, and firm size. The macro variables include log (GDP), log (PCI), linguistic distance with the U.S., religion distance with the U.S., legal origin, landlockedness, tropical land area, absolute latitude and continent dummy. Robust standard errors for the 2SLS and bootstrap standard errors for the quantile estimates are reported in the parentheses. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

7.6.1 Alternative Measure of Productivity

To examine the robustness of our baseline results to the measurement of TFP, we also use the World Bank's (2017) revenue based measure of total factor productivity measure (TFPR) that excludes material inputs.

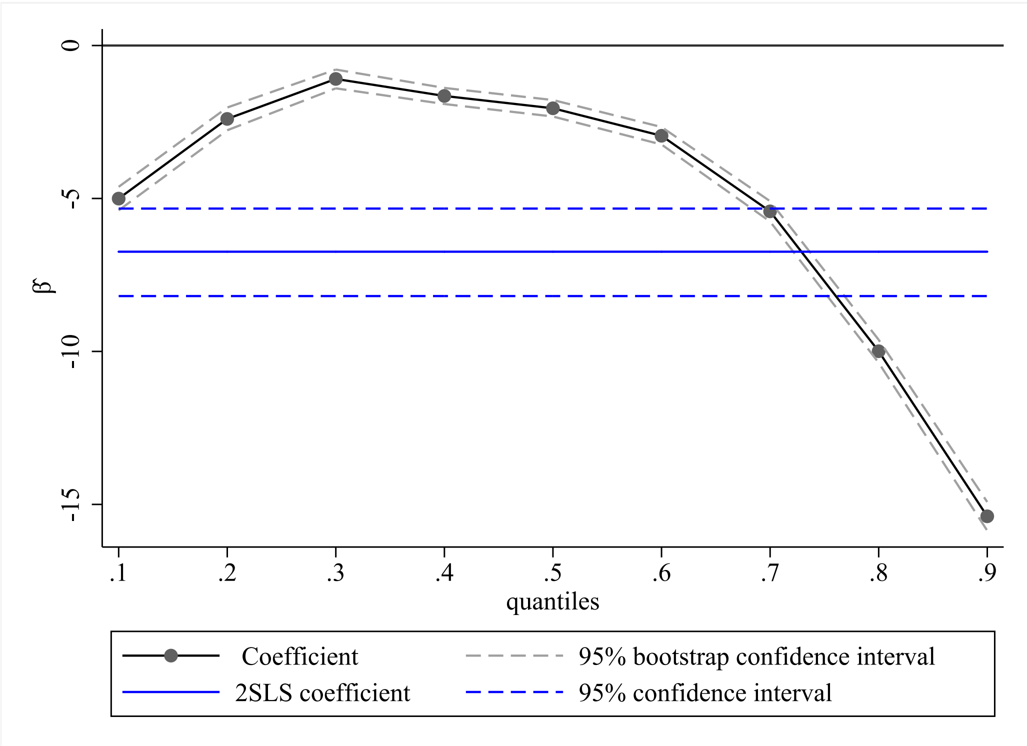
Table 7.3 and Figure 7.3 present the effect of genetic distance at the mean (2SLS) and across the distribution of TFPR, after controlling for all micro- and macro-level covariates. As before, column (1) presents the 2SLS estimate while column (2) to (6) report the estimated quantile coefficients. Robust standard errors are reported for 2SLS estimate, whereas bootstrap standard errors are used for the quantile estimates. As seen, the results are qualitatively the same as in the case of the TPF measure with material inputs included (see Table 7.2 vs. Table 7.3 and Figure 7.2(b) vs. Figure 7.3). In particular, the impact of genetic distance across the distribution of TFPR is an inverted U-shape,thus confirming that the relationship between genetic distance and TFPR is not monotonically decreasing as the 2SLS estimate tends to suggest. In general, the effects of genetic distance tend to be deeper on the distribution of TFPR than that of TFP (see Table 7.3 vs. Table 7.2), especially at the top quantiles. In addition, while the impact of genetic distance across the distribution of TFP is a near inverted U-shape, that on TFPR is an inverted U-shape, thus supporting our main result that there is a (quasi-)inverted U-shaped relationship between firm technology adoption and genetic distance.

Table 7.3: Revenue Based Measure of Total Factor Productivity (TFPR)

	(1)	(2)	(3)	(4)	(5)	(6)
		Quantiles				
	2SLS	0.10	0.30	0.50	0.70	0.90
F_{ST} gen. dist. to the US, weighted	-4.88***	-5.00***	-1.09***	-2.05***	-5.42***	-15.39***
	(0.6848)	(0.19604)	(0.1567)	(0.1373)	(0.1697)	(0.2382)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic covariates	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Number of countries	94	94	94	94	94	94
Number of firms	30,474	31,142	31,142	31,142	31,142	31,142

Note. The micro variables include age, export dummy, firm ownership, and firm size. The macro variables include linguistic distance with US, religion distance, legal origin, landlockedness, tropical land area, absolute latitude, continent dummy, log of average RGDP, log of average RGDP per capita, log of tertiary education and log of average openness. Robust standard errors for the 2SLS and bootstrap standard errors for the quantile are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Figure 7.3: Effect of Genetic Distance on TFPR



7.6.2 Alternative Measure of Genetic Distance

In the previous sections, we consider the US as the global technology frontier. However, several technologies were also invented in other advanced societies (Ang and Kumar, 2014) and assuming the US is the only global leader in technology may be too restrictive. To investigate the sensitivity of our results to the choice of the world leader, we use the United Kingdom (UK) as an benchmark world technology frontier. This choice is supported by Ang and Kumar (2014) and the data on weighted genetic distance of laggard countries from the UK are from Bove and Gokmen (2017).

Figure 7.4 and Table 7.4 presents the estimated impact of genetic distance on TFP. As seen, the results are very similar to the baseline ones with the US as the technology frontier; see Section 7.6. In particular, the near inverted U-shaped impact of genetic distance across the distribution of TFP is clearly demonstrated, thus indicating a non-monotonic relationship between genetic distance and the diffusion of technology.

Overall, the results of this section underscore the fact that our previous analysis in Section 7.6 are not driven by the choice of the global technology leader.

Figure 7.4: Effect of Genetic Distance from UK on Firm Productivity

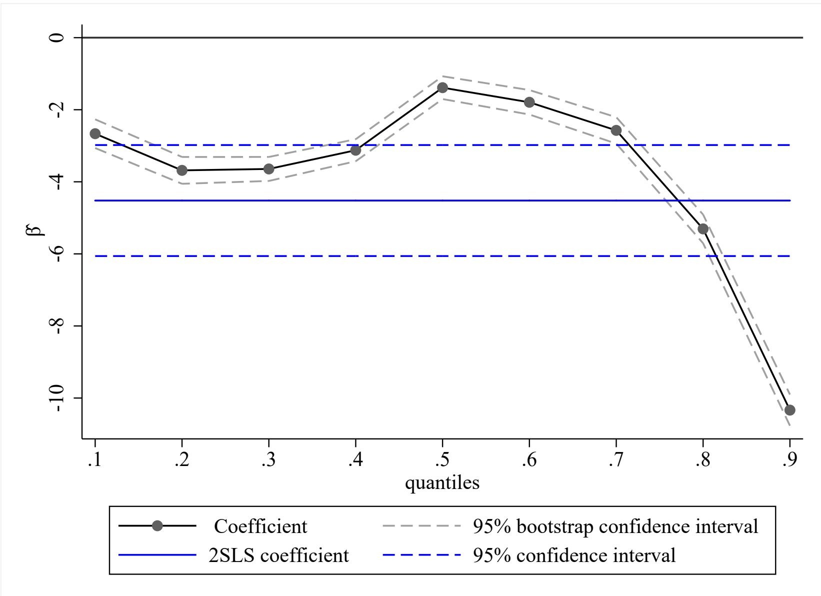


Table 7.4: Alternative Measure of Genetic Distance

	(1)	(2)	(3)	(4)	(5)	(6)
		Quantiles				
Group IV Quantile	2SLS	0.10	0.30	0.50	0.70	0.90
F_{ST} gen. dist. to	-4.52***	-2.66***	-3.64***	-1.39***	-2.57***	-10.34***
the UK, weighted	(0.7872)	(0.2028)	(0.1699)	(0.1609)	(0.1868)	(0.2205)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic covariates	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Number of countries	94	94	94	94	94	94
Number of firms	31,212	31,500	31,500	31,500	31,500	31,500

Note. The micro variables include age, export dummy, firm ownership, and firm size. The macro ones include linguistic distance with the US, religion distance, legal origin, landlockedness, tropical land area, absolute latitude and continent dummy, log of average RGDP, log of average RGDP per capita, and log of tertiary education. Robust standard errors for 2SLS and bootstrap standard errors for quantile estimates are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

7.7 Other Robustness Checks

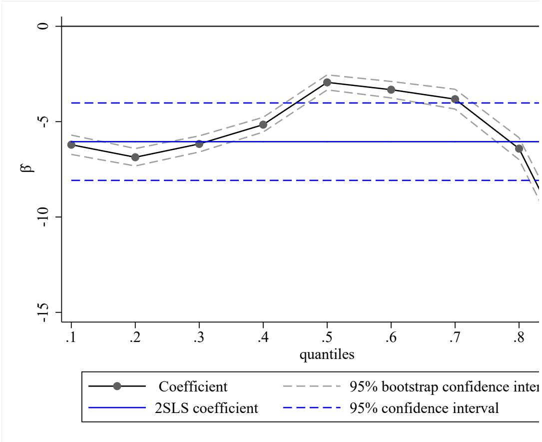
In this section, we investigate the robustness of our results to the inclusion of additional covariates and the relative weight of European countries in the sample.

7.7.1 Controlling for Additional Covariates

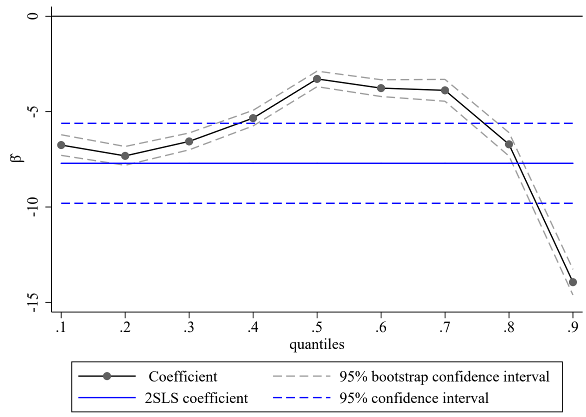
Spolaore and Wacziarg (2009) and Ang and Kumar (2014) highlight that technology diffusion has increased for more open economies. Therefore, the transfer of technology may be higher for countries that have good quality of institution, even after controlling for geographic and cultural factors, human capital, language and religion distance, and continent dummies, as done in Section 7.5. As such, it is important to check whether the trade openness and the quality of institutions alter our baseline results of Section 7.5. To address this concern, we also control for trade openness and institutional quality in the baseline regression. Both covariates are included in our sample.

Table 7.5 presents the estimated impact of genetic distance at the mean (2SLS) and across the distribution of TFP when trade openness and institutional quality are also controlled for. *Panel (A)* reports the results when only trade openness is controlled for, while *Panel (B)* shows the results when both trade openness and institutional quality are included. In all cases, both the 2SLS and quantile estimates of the impact of genetic distance on TFP are similar to our baseline results of Section 7.5. Interestingly, controlling for trade openness and institutional quality has even strengthened the impact of genetic distance on technology adoption, both at the mean (2SLS) and across the distribution of TFP, thus suggesting that our baseline results are not driven by the degree of globalization or institutional quality across countries. Furthermore, Figure 7.5, again, illustrates the appealing finding that the relationship between genetic distance and the distribution of TFP is a near inverted U-shape. As such, we clearly see that the 2SLS method under-and over-estimate the impact of genetic distance at important parts of the distribution of TFP. In particular, it is clear from Figure 7.5(b) that a country with a low technology adoption (ranked between 0–30th quantile) and a country with moderate technology adoption (ranked between 30th–50th quantile) or relatively high technology adoption (ranked between 50th–70th) can be impacted identically by the same shock on current genetic distance.

Figure 7.5: Genetic Distance vs. Trade Openness and Institutional Quality



(a) Trade openness only



(b) Trade openness and institutional quality

Table 7.5: Controlling for Additional Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
		Quantiles				
Panel A: controlling for openness only	2SLS	0.10	0.30	0.50	0.70	0.90
F_{ST} gen. dist. to the US, weighted	-6.05***	-6.21***	-6.17***	-2.94***	-3.82***	-13.10***
	(1.0377)	(0.2583)	(0.2153)	(0.2009)	(0.2647)	(0.3171)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic covariates	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Number of countries	94	94	94	94	94	94
Number of firms	30,885	31,142	31,142	31,142	31,142	31,142
Panel B: controlling for openness and Institution						
F_{ST} gen. dist. to the US, weighted	-7.71***	-6.75***	-6.56***	-3.28***	-3.88***	-13.94***
	(1.0696)	(0.2754)	(0.2251)	(0.2077)	(0.2920)	(0.3426)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic covariates	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	94	94	94	94	94	94
Number of firms	30,885	31,142	31,142	31,142	31,142	31,142

Note. The micro variables include age, export dummy, firm ownership, and firm size. The macro ones include linguistic distance with US, religion distance, legal origin, landlockedness, tropical land area, absolute latitude, continent dummy, log of average RGDP, log of average RGDP per capita, log of tertiary education and log of average openness. Robust standard errors for 2SLS and bootstrap standard errors for quantile estimates are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

7.7.2 Excluding European Countries

We investigate the stability of our baseline results to the exclusion of European countries from the sample. There are two main reasons to do so. First, the measurement error in genetic distance data for Europe is relatively smaller as the sample populations almost match the nation-state boundaries (Spolaore and Wacziarg, 2009). Second, technology spreads more easily to the east-west direction which makes European countries more advantageous over more isolated countries (such as Australasia) and over continents that are located to the north-south axis (such as Africa and Latin America); see Diamond and Renfrew (1997). The latter hypothesis is well known as "the Diamond gap." Therefore, by excluding Europe from the sample, we can: (i) check the stability of our baseline results when only the countries with a relatively larger measurement error in the genetic distance data are used; and (ii) test whether our baseline results are driven by the Diamond gap.

Figure 7.6: The Effect of Genetic Distance on Firm Productivity

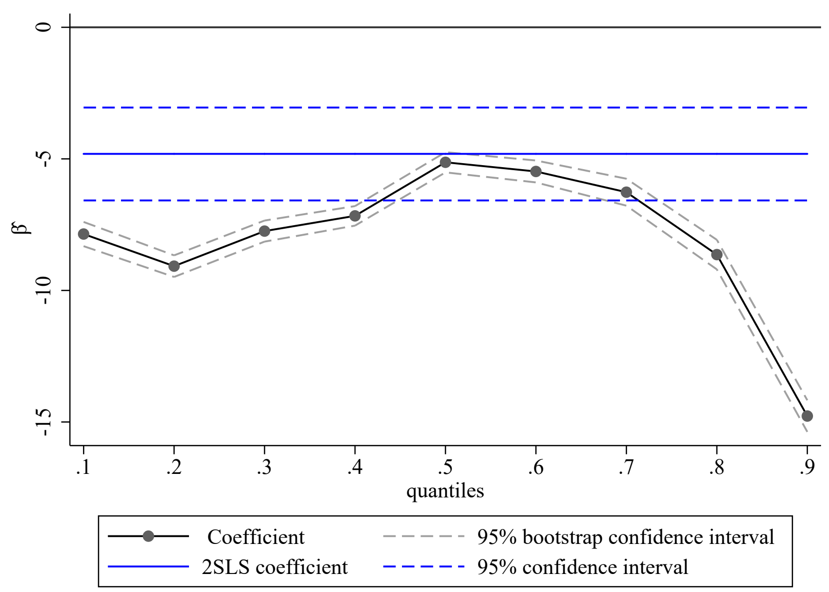


Table 7.6 and Figure 7.6 presents the results. Consistent to our baseline results, genetic distance has a large negative effect on firms' productivity at the higher quantiles. Moreover, all the quantile estimates are larger in magnitude and statistically significant at 1% nominal level compared with our baseline results of Section 7.5. A close inspection of both the 2SLS and quantile estimates suggests that 2SLS under-estimates the effect of genetic distance at lower and higher parts of

Table 7.6: Excluding Europe

	(1)	(2)	(3)	(4)	(5)	(6)
			Quantiles			
Group IV Quantile	2SLS	0.10	0.30	0.50	0.70	0.90
F_{ST} gen. dist. to	-4.81***	-7.86***	-7.74***	-5.13***	-6.27***	-14.77***
the US, weighted	(0.8997)	(0.2348)	(0.2044)	(0.1956)	(0.2613)	(0.3062)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Number of countries	84	84	84	84	84	84
Number of firms	29,310	28,997	28,997	28,997	28,997	28,997

Note. The micro variables include age, export dummy, firm ownership, and firm size. The macro variables include linguistic distance with US, religion distance, legal origin, landlockedness, tropical land area, absolute latitude, continent dummy, log of average RGDP, log of average RGDP per capita, log of trade openness and log of tertiary education. Robust standard errors for the 2SLS and bootstrap standard errors for the IV quantile are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

the distribution of TFP due the near inverted U-shape property of the relationship between the two. Clearly, our baseline results are not driven by measurement error in the genetic distance data or the Diamond gap.

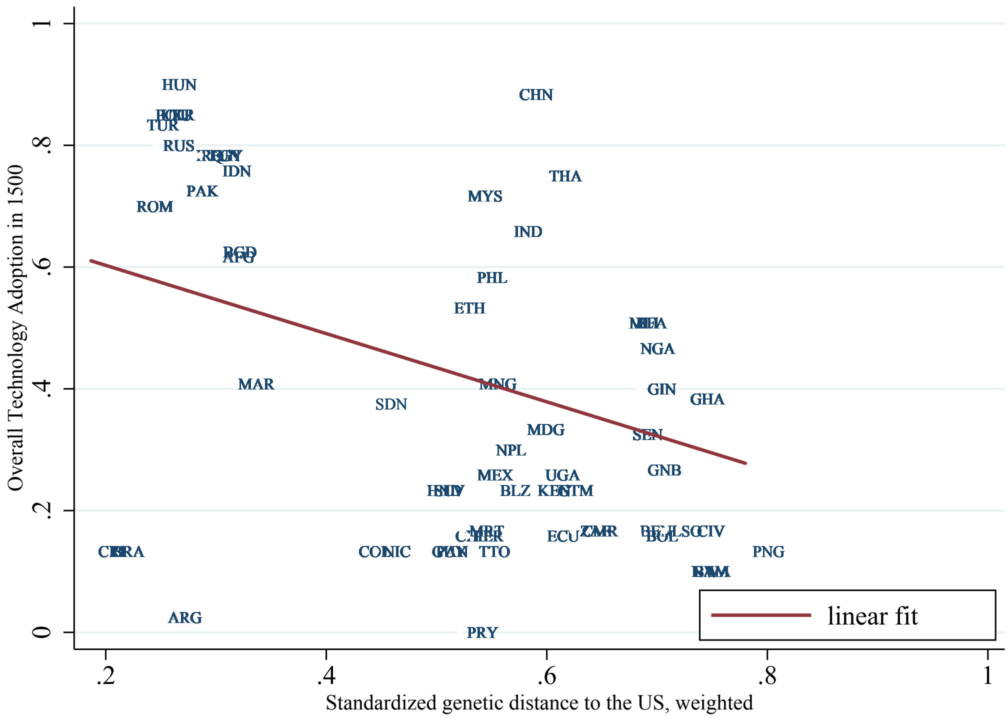
7.8 Genetic Distance, Technology Adoption, and TFP

Section 7.5 established a robust negative and near inverted U-shape effect of genetic distance along the distribution of firms' productivity across countries. One may argue that the specification (7.19)-(7.20) that led to this result is a reduced-form, thus be willing to provide an endogenous mechanism through which genetic distance impacts on firms' TFP. Such a chain of causality could be that genetic distance influences firms' productivity through technology adoption, but this is yet to be formally demonstrated. Our goal in this section is not to provide a definitive answer to the effectiveness of such a mechanism, rather we offer suggestions that could help to advance future research in that direction.

Previous studies documented that genetic distance is one of the persistent barriers to contemporary technology adoption (Spolaore and Wacziarg, 2009; Ashraf and Galor, 2013a). Along the same vein, Figure 7.7 shows the scatter plots between country-level measures of historical technology adoption in 1500AD and standardized genetic distance to the world leader, the US. The technology option data consists of 24 technologies provided by Comin and Hobijn (2010). In this dataset, the 24 technologies are classified in five broad sectors: agriculture, industry, transportation, communication, and military. Each technology is measured as a binary variable indicating whether it was present in a given country in 1500AD. Comin and Hobijn (2010) combined them into one factor labeled '*Overall technology adoption in 1500*' (see the y-axis of Figure 7.7). This factor is simply compute as the sample average across sectors of the technology adoption levels. As it can be seen from that graph, the standardized genetic distance is negatively correlated with the overall technology adoption in the 1500AD, thus corroborating the findings of Spolaore and Wacziarg (2009) and Ashraf and Galor (2013a). To examine how this relationship has evolved over time, Figure 7.8 depicts the scatter plots between the two variables in the 2000AD for all countries in the sample. Again, the figure shows a negative correlation between genetic distance and overall technology adoption in the 2000AD, thus highlighting the persistence of their relationship over time.

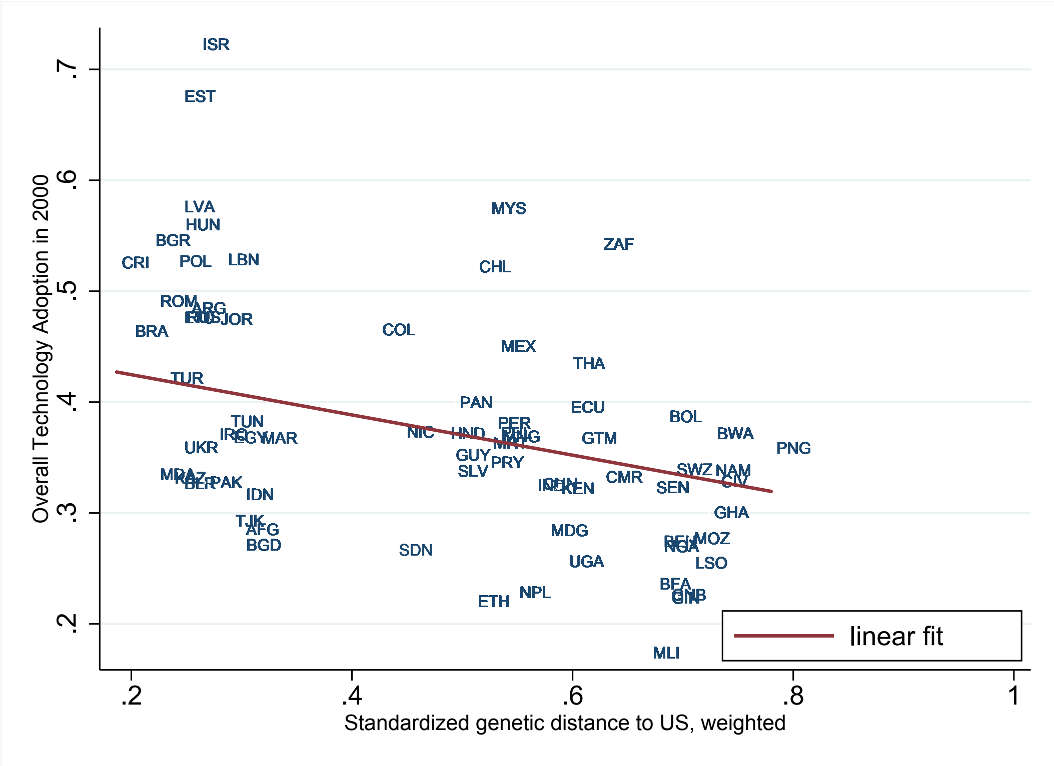
In our sample, countries such as Ethiopia, Nepal, Burkina-Faso and Mali have 0.509, 0.574, 0.674, and 0.668 respectively as standardized measure of genetic distance, thus can be classified as having less genealogical similarities with the US. Yet unsurprisingly these countries had the lowest overall technology adoption level in the 2000AD. For example, the four countries (Ethiopia, Nepal, Burkina-Faso, Mali) had an overall technological adoption around 0.533, 0.3, 0.508, and 0.508 respectively in the 1500AD, which has eroded to about 0.220, 0.228, 0.236 and 0.173 respectively in the 2000AD. Meanwhile, Argentina, for example, which is genealogically close to the US (with standardized genetic measure of 0.249) has moved from 0.02 overall technology adoption in the 1500AD to about 0.484 in the 2000AD.

Figure 7.7: Genetic Distance and Overall Technology Adoption in 1500AD



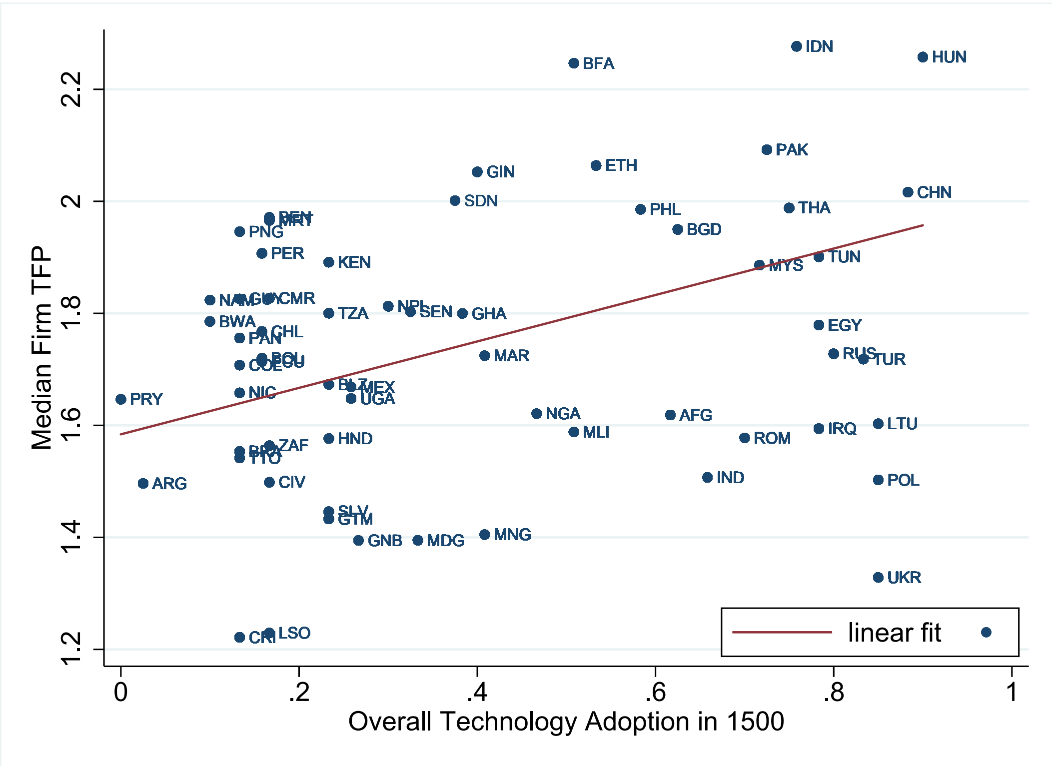
Figures 7.9 shows the scatter plots between overall technology adoption in the 1500AD and current median firms' TFP for all countries in the sample. As seen, overall technology adoption in the 1500AD is strongly positively correlated with current median firms' productivity. Since current genetic distance is negatively correlated with overall technology adoption in the 1500AD (as documented in Figures 7.7 & 7.8), we expect current genetic distance to have a negative impact on the

Figure 7.8: Genetic Distance and Overall Technology Adoption in 2000AD



distribution (at least the median) of firms' TFP, thus corroborating our main findings in Section 7.5. It is nonetheless important to note that the analysis in Figures 7.7-7.9 is only based on correlations, so more investigations are required to clarify if genetic distance influences firms' productivity through its impact on the technology adoption in the 1500AD. We leave these investigations for future research.

Figure 7.9: TFP and Overall Technology Adoption in 1500AD



7.9 Conclusion

This paper exploits the theoretical framework of Comin and Hobijn (2010) to propose a mechanism through which genetic distance from the world leader, the US, acts as a barrier to technology adoption in laggard countries, thus impacting negatively on firms' TFP in those countries. There are some challenges in testing this theory empirically, and we elaborate on how those challenges can be circumvent. First, the treatment variable (genetic distance) is measured at country-level while the outcome variable (firm productivity) is available at firm-level, which makes the standard panel data method useless in identifying the causal effect since the treatment variable will be dropped out after a within-type transformation. Second, there is a substantial heterogeneity across the distribution of firms' productivity, hence a mean-type regression analysis is not appropriate. Third, due to the presence of group-level unobservables in the model (country fixed effect), a standard quantile regression such as in Koenker and Bassett Jr (1978) will yield inconsistent estimates, thus is not also appropriate in dealing with this type of problems.

Using a novel method on quantile treatment models with group-level unobservables recently proposed by Chetverikov et al. (2016) that accommodates the above problems, we show that the impact of genetic distance on firm productivity is consistently negative and *near inverted U-shaped* across the distribution of firms' TFP. This means that firms operating in countries genealogically far from the technology leader tend on average to have lower level of productivity, but firms in two countries, one with a very low technology adoption and the other with a moderate or relatively high technology adoption can be impacted identically by the same shock on current genetic distance. This may justify why some countries that appear genealogically closer to the US have not benefited from technology adoption compared with their peers that are far from the US, or vis-versa. We provide several robustness checks that show that the near inverted U-shape property of the relationship between genetic distance and the distribution of firms' TFP is robust: (i) to alternative measures of productivity and genetic distance; (ii) to inclusion of institutional quality and trade openness in the model; (iii) to the exclusion of

European countries whose genetic data are likely less measured with errors than non-European countries.

References

Ang, J. B. and S. Kumar (2014). Financial development and barriers to the cross-border diffusion of financial innovation. *Journal of Banking & Finance 39*, 43–56.

Ashraf, Q. and O. Galor (2013a). Genetic diversity and the origins of cultural fragmentation. *American Economic Review 103*(3), 528–33.

Ashraf, Q. and O. Galor (2013b). The 'out of Africa' hypothesis, human genetic diversity, and comparative economic development. *American Economic Review 103*(1), 1–46.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review 103*(1), 305–34.

Bove, V. and G. Gokmen (2017). Genetic distance, trade, and the diffusion of development. *Journal of Applied Econometrics*.

Chetverikov, D., B. Larsen, and C. Palmer (2016). IV quantile regression for group-level treatments, with an application to the distributional effects of trade. *Econometrica 84*(2), 809–833.

Comin, D. and B. Hobijn (2010). An exploration of technology diffusion. *American Economic Review 100*(5), 2031–59.

Comin, D. and M. Mestieri (2014). Technology diffusion: measurement, causes, and consequences. In *Handbook of economic growth*, Volume 2, pp. 565–622. Elsevier.

Comin, D. A. and M. M. Ferrer (2013). If technology has arrived everywhere, why has income diverged? Technical report, National Bureau of Economic Research.

Diamond, J. and C. Renfrew (1997). Guns, germs, and steel: the fates of human societies. *Nature 386*(6623), 339–339.

Foster, L., J. C. Haltiwanger, and C. J. Krizan (2001). Aggregate productivity growth: Lessons from microeconomic evidence. In *New developments in productivity analysis*, pp. 303–372. University of Chicago Press.

Giuliano, P., A. Spilimbergo, and G. Tonon (2006). Genetic, cultural and geographical distances.

Guiso, L., P. Sapienza, and L. Zingales (2009). Cultural biases in economic exchange? *The Quarterly Journal of Economics 124*(3), 1095–1131.

Hall, R. E. and C. I. Jones (1999). Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics 114*(1), 83–116.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Hsieh, C.-T. and P. J. Klenow (2010). Development accounting. *American Economic Journal: Macroeconomics 2*(1), 207–23.

Jäggi, A., S. Legge, and L. Schmid (2018). Dyadic value distance: Determinants and consequences. *Economics Letters 165*, 48–53.

Kato, K. and A. F. Galvao (2011). Smoothed quantile regression for panel data.

Kato, K., A. F. Galvao, and G. V. Montes-Rojas (2012). Asymptotics for panel quantile regression models with individual effects. *Journal of Econometrics 170*(1), 76–91.

Koenker, R. and G. Bassett Jr (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, 33–50.

Midrigan, V. and D. Y. Xu (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review 104*(2), 422–58.

Proto, E. and A. J. Oswald (2017). National happiness and genetic distance: A cautious exploration. *The Economic Journal 127*(604), 2127–2152.

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics 11*(4), 707–720.

Spolaore, E. and R. Wacziarg (2009). The diffusion of development. *The Quarterly Journal of Economics 124*(2), 469–529.

Spolaore, E. and R. Wacziarg (2016). Ancestry and development: New evidence. *Journal of Applied Econometrics*.

Spolaore, E. and R. Wacziarg (2017). Ancestry and development: New evidence. *UCLA CCPR Population Working Papers*.

Syverson, C. (2004). Product substitutability and productivity dispersion. *Review of Economics and Statistics 86*(2), 534–550.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature 49*(2), 326–65.

World Bank (2017). Firm level productivity estimates. Technical report.

Appendix A: Variable Definition

Table A1: Variable Definition

Variables	Definition
TFP	Firm -level estimates of total factor productivity
Genetic distance to the US or UK	The genetic distance between the current population of a given country and the US (or UK). It is calculated as the average pairwise genetic distance across all ethnic group pairs. It captures the general relatedness of the population of a particular country to US or UK
Genetic distance to the UK (1500 AD)	The genetic distance between the populations of a given country and the UK in the year 1500, prior to the major colonizations of modern times & migration calculated as the genetic distance between the two ethnic groups comprising the largest shares of each countrys population in the year 1500
Technology adoption (1500 Ad)	The overall adoption level is computed as the average of the sectoral adoption levels, where sector adoption levels is the simple average of the binary adoption values across the technologies in the sector in 1500
Technology adoption (2000)	The overall adoption level is computed as the simple average of the sectoral adoption levels, where sector adoption levels is the simple average of the binary adoption values across the technologies in the sector in 2000
GDP	Average gross domestic product (2000-2005)
PCI	Average GDp per capital (2000-2005)
Export dummy	=1 if a firm export
Foreign	=1 if the firm has at least 10% of its equity held by foreigners
Small	=1 if the firm has 5-9 employee
Medium	=1 if the firm has 10-99 employee
Large	=1 if the firm has above 99 employee
Geographic distance	Measure of the great circle (geodesic) distance between the major cities of countries
Religious distance	Measure of religious relatedness based on a nomenclature of world religions
Legal origen	Dummy variable that takes a value of one if a countrys legal system is of French, German or Scandinavian Civil Law origin and zero otherwise
Landlockedness	=1 if a firm is operating in a landlocked country
Tropical	The % of land area classified as tropical and subtropical based on the Koeppen-Geiger system
Latitude	Absolute value of the latitude of a country, scaled between zero and one, where zero is location on the equator and one is for the poles

Chapter 8

Concluding Remarks

This thesis explores the underlying causes of civil conflict and economic development in developing countries. Economic shocks are shown to be crucial causes of civil conflict. The idea is that negative economic shocks reduce the opportunity cost of fighting which raises the likelihood of civil conflict. Several empirical studies provide strong evidence to support the opportunity cost hypothesis using negative income shocks such as international commodity price shocks, rainfall shocks and interest rate shocks. Similarly, a large and growing number studies consider that institution, geography, and culture are the deep and fundamental sources of economic development. Despite a plethora empirical evidence on the underline causes of civil conflict and economic development in poor countries, providing riveting explanations using more credible econometric methods that establish causality has become a more promising avenue of empirical research. As such, the thesis has sought to shed some light on the root causes of civil conflict, trade, foreign direct investment and productivity by employing modern impact evaluation econometric approaches.

Chapter 2 explores the impact of economic shocks that are related to RER misalignment on the likelihood of civil conflict in sub-Saharan Africa. To do so, we construct a RER misalignment measure that is driven by the short-run shocks of foreign RER fundamentals. We found that RER over-valuation considerably raises the probability civil conflict: a one standard increase in RER misalignment raises civil conflict by about 4 percentage point. More importantly, the effect RER misalignment significantly bigger than the effect of rainfall shock and international commodity price shocks–which are the two most common causes of conflict in the region. Besides, we construct the traditional RER misalignment index that is consistent to the RER theory and using the instrumental variable approach we find qualitatively similar results with the baseline. As such, the findings suggest that stabilizing the RER to the equilibrium level not only increase economic growth but also fosters economic development by reducing civil conflict in the region.

In chapter 3, we investigate the causal impact of food aid on the incidence of civil conflict in SSAs. In this chapter, we propose a novel identification strategy (i.e. instrumental variable) to address the endogeneity problem in the existing foreign aid literature. Employing the number of affected people by natural disaster in other SSA countries as an instrumental variable (IV) to aid, we find that food aid has no a statistically significant effect on increasing civil conflict in the region. The findings also show that civil conflicts spillover to neighboring SSA countries after two years. Some of the channels through which civil conflict may diffuse to other SSA countries are ethnic connection, migration, and poor institutional qualities. Hence, the findings suggest that food aid is still an important international development policy tool to fight hunger and suffering in developing countries.

The integration of developing countries with advanced countries is crucial for economic development. However, the economic integration may be deterred by a range different factors. Chapter 4 commences the discussion on this topic by comparing the effect of inflation targeting (IT) and fixed exchange rate monetary policy rules in attracting FDI in the context of developing countries. To address the issue of self-selection by countries into the inflation targeting or fixed exchange rate regime, we implement the propensity score matching and the difference-in-differences estimation approaches. The estimates show that as long as one of these policies is pursued, there is no perceivable advantage in adopting inflation targeting over a fixed exchange rate (and vice-versa) for attracting FDI.

Likewise, chapter 5 extends the discussion on the key determinants of economic integration by investigating the the causal effect of geographical impediments on trade. This chapter focuses on examining the causal impact of landlockedness on disaggregate export and import in Ethiopia. Exploiting the de facto landlockedness of Ethiopia in 1998 and using a triple difference-in-differences strategy, we find that landlockedness has a large negative and statistically significant effect on the import and export of several goods. Overall, the dynamic impact of loosing access to the port also increase overtime. Similarly, chapter 6 explores the causal impact of establishing agricultural commodity exchange in improving the export quantity of agricultural export commodities. Following the establishment of the Ethiopia Commodity Exchange (ECX) in 2008 and exploiting the sudden introduction of coffee in the ECX market, the estimated results show that ECX has a strong impact in increasing coffee export. As such, agricultural markets may assist in reducing poverty in LDCs by raising primary commodity export.

Finally chapter 7 analyzes the the role of deep-rooted historical factors on the diffusion of technology from the technology frontier to laggard countries. This chapter has two major contributions to the literature. First, it provides micro channel evidence through which genealogical distance reduces the diffusion of technology from the technology frontier to the adopter countries. Second, it investigates the distributional impact of genetic distance on the productivity of firms. Employing the survey data of more than 32,000 firms and group quantile IV (GQIV) estimator, we find that the effect of genetic distance is bigger for more productive firms. The findings provide an underlying mechanism for the earlier empirical studies in such a way that cultural differences reduce the flow of technology to firms (which reduce firm productivity) and hence the diffusion of development for the country.