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Essays on immigrant integration, remittances, and agricultural policies in developing countries.

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Abstract

This thesis is mainly organise into two parts; the first part relates to immigrants - their economic integration in the host country and their role in mitigating the effect of disasters in their home countries through remittances. The second part of this thesis is a policy evaluation of the effect of export bans on prices and food security.

In the first chapter, I describe and investigate the role of informal institutions in the labour market integration of immigrants. I exploit a law in France, that was implemented in 1981 when the socialist government came to power, which allowed individuals including immigrants to organise themselves into groups or associations. North African immigrants mainly originating from Morocco, Tunisia and Algeria capitalised on this law to establish several community based organisations in various locations in France. A particular type that is of interest to this paper are those engaged in the economic integration of immigrants. These organisations mainly seek to assist immigrants in improving their labour market outcomes through the provision of language training classes, CV preparations, information about job opportunities and so on.

I collect information on all such organisations registered in France between 1996 - the year in which the first organisation was recorded to 2012. I combine it with data from the French labour force survey between 1990 and 2012 to asses its effect on labour force participation, employment, and earnings of these immigrants using a difference-in-differences strategy combined with a Heckman selection model. I find that these organisations improve labour force participation rates and the probability of obtaining a job for Maghreb women without a corresponding reduction in earnings.

In the second chapter, using monthly remittance flows from Italy to a number of developing countries, we investigate the impact of natural disasters on remittances with the aim of improving identification by adapting an event study design. This allows us to flexibly document the immediate response of remittances and to test if there exists any anticipatory or lag effect in the way in which remittances responds to natural disasters. The use of monthly data further allows us to clearly distinguish the response of remittances depending on the nature of the disaster. Our analyses uses various alternative specifications of the disaster measure and varying lengths of the response period.

Our findings reveal that remittances increases significantly in the months following the

occurrence of a disaster peaking at an average of 2.7 percent, four months following the disaster and averaging about 2 percent over the 12 months window. Controlling for disasters occurring outside our sample period to eliminate any remaining trend in remittance flows and capture any potential dynamics that might be attributed to disasters does not affect neither the magnitude or significance of our coefficients, rather it allows for a clear breakthrough in the dynamics of remittance flows around the time of the disaster. All our findings are robust to controlling for other shocks in the receiving country such as the trend and cyclical fluctuation in the monthly terms of trade, monthly rainfall and temperature as well as a proxy for the economic condition in the sending country and a host of country and time fixed effects.

Further carrying out several heterogeneity analyses reveal that the response of remittances is higher for countries with a relatively larger stock of immigrants and that the observed effect is largely driven by the response to disasters occurring in upper middle-income developing countries. We also find a differential response in timing based on the nature of the disaster, slow or sudden.

Finally, in the third chapter I conduct a policy evaluation of the effect of an export ban on maize instituted by the Malawian government. Using monthly price and annual harvest data from the Malawian ministry of agriculture, I investigate the effect of the policy on maize prices and its volatility as well as on maize production. I extend this literature by further distinguishing the export bans based on whether they are internally induced - supply shock or externally induced demand shock. To account for the endogeneity of the ban, I Use monthly rainfall data and global maize prices as instruments for the ban.

I find the export bans on aggregate to be unsuccessful in preventing a rise in maize prices, though to some extent it stabilises maize prices. Once we distinguish the ban based on factors inducing it, we find two opposing results. First, that export bans are ineffective against a demand induced export ban but very effective against a supply induced export ban. Based on anecdotal evidence, it seems that traders hoard these goods in anticipation of a lifting of the ban to get access to better prices for their products, hence the ineffectiveness f the ban in the midst of rising global prices. Furthermore, there is also evidence that despite the ban, positive quantities of maize continues to be exported illegally rendering the policies ineffective and thereby failing to mitigate the effect of the shock on prices.

In terms of food security, we use the share of acreage dedicated to maize production as a proxy for food security. Here, I argue that the ad-hoc nature in which the policy is imposed and lifted creates a source of uncertainty in maize prices which may have consequent effect on farmers maize cultivation decisions, especially for large scale commercial farmers. Estimating a dynamic system GMM model, I find that the ban induces farmers to reduce the acreage share allocated to maize production. However, since we do not observe the variety of maize being cultivated or the inputs used in production, we cannot really conclude on whether there is a decline in maize production or a shift towards cultivating higher yielding maize varieties.

Dedication

To my late mother Jainabou Jallow (may Allah have mercy on your departed soul), my stepmother, Ragiatou Jallow - Yayeh as she is fondly called and my father Abdoulie Jallow.

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Chapter 1

Informal institutions and immigrants economic integration

Abstract

This study is primarily motivated by concerns about immigrants economic integration and efforts taken by immigrants themselves to improve there labour market prospects. I combine data from the french labour force survey from 1990 to 2012 with an original data-set of Maghreb immigrants informal institutions registered in France for the same period. These institutions are mainly established to help migrants integrate successfully in the French labour market. I apply a double-differences strategy to investigate the effect of these institutions on labour force participation, employment and wages of Maghreb immigrants. I find that the presence of these institutions in a french department is associated with an increase in labour force participation and greater employment prospects for Maghreb women.

1.1 Introduction

Enhancing the cultural and economic integration of immigrants as highlighted in various policy report documents is fundamental in fully harnessing the gains from migration. Immigrants that are well integrated in the labour market are able to earn higher incomes which translate to net fiscal gains for the host countries, positively influencing attitudes of natives towards immigrants and immigration policy (Borjas (2015), Cuaresma et al. (2015)), and potentially increasing remittance transfers both for family consumption and for the development of origin communities (see (Portes et al. (2007) and Chauvet et al. (2015)). On the contrary, poor integration makes migrant to become competitors rather than complements to natives thus aggravating rather than alleviating social tensions and labour market problems.

Despite the benefits associated with a well integrated immigrant labour force, the economic situation of first and second generation immigrants in the labour force is still poor relatively to natives. For instance, at the EU level, labour force participation rates of migrants were about 8% lower than that of EU citizens in 2012 up from 6% in 2008 and has deteriorated to about 12% by the end of 2015. Similarly, unemployment rates for immigrants relative to native Europeans in the labour force were about 9% higher in 2012 from a little less than 6% in 2008, though this gap has slightly narrowed by the end of 2015 to about 8.7% (Eurostats 2016). Moreover, Significant heterogeneity exists based on age, gender and country of origin. For instance women and young immigrants are even more less likely to participate in the labour market outcomes than those coming from within the OECD. A greater concern is the fact that some second generation immigrant groups tend to perform worst in the labour market than their parents despite been born, raised and schooled in the host country. This is particularly true for some non-OECD immigrants in France, Germany and the UK (Algan et al. (2010a)).

The assimilation and cultural integration of immigrants have been mainly studied by sociologist focusing on aspects like age of marriage, fertility rates and inter-ethnic marriages. These studies find that immigrants outcomes are slowly but closely approaching those of natives (Cul (2012)). Other studies have focused on the effect of "ethnic enclaves" and the role of social networks in improving labour outcomes (Munshi (2003)). Most of the research has been centred on Mexican migrants in the U.S. and the main labour outcomes studied are wages, employment and occupational mobility as measures of economic integration. The results generally finds that social networks helps to improve labour market outcomes of immigrants by increasing the chances of being employed and raising earnings through its role on facilitating occupational mobility (see Borjas (1992), Munshi (2003), Amuedo-Dorantes and Mundra (2007), Chiswick and Miller (2002a), Damm (2009), Drever and Hoffmeister (2008), Danzer and Ulku (2011)). However, as one would expect the role of this informal social networks are mostly limited to providing information within a very closed network.

In France a more formalised version of this social networks has emerged as a result of a law by the socialist government allowing individuals to freely organise themselves into groups. Migrants coordinate and organise themselves to create Community Based Organisation's (CBO's) aimed at improving their welfare. One that is of particular interest to this paper are those engage in the integration of immigrants. Migrant CBO's also known as associations¹ engage in integration, like Home Town CBO's $(HTA)^2$ are voluntary groups established by immigrants in their host countries mostly gathering immigrants from the same origin country with the main aim of improving labour outcomes of immigrants. They are becoming influential and their activities are increasingly being recognised by stakeholders in the integration process including governments of both source and host countries as well as international organisations. For instance, in Spain they were actively involved in raising awareness on the need for integration and crafting the Spanish integration model (Hector et al (forthcoming)). Among other things, they mainly assist immigrants in providing language training classes, CV preparations, providing information on availability of job opportunities and so on. Among the reasons for the increase in optimism of the role of this CBO's stems from their close proximity to the targeted immigrants which gives them a first hand knowledge of the problem faced by immigrants thus allowing them to provide tailor made solution to meet their specific needs.

However, from a theoretical point of view their impact is not straight forward. First, instead of providing information about job opportunities, this CBO's might instead provide information on how to access welfare benefits. Thus increasing reservation wages of immigrants, discouraging work and thereby leading to increase dependence on the state . Secondly, instead of providing complementary skills that are relevant to the labour market such as helping those with limited french speaking skills improve their language skills, they might indirectly provide a disincentive for them to learn the language since they can converse in their common local language. Thirdly, due to their limited financial capacity, this CBO's might not be as effective as other public actors such as the high council for economic integration (HEC) in France. Besides, their objectives and activities might be influenced by other outside actors such that they are forced to aligned their activities to the interest of the donors or partners rather than pursuing the interest of the immigrants. This may limit them from realising their full potentials.

Notwithstanding, the role played by this CBO's in the economic integration of immigrants has not been empirically and systematically investigated. So far, little empirical evidence exists as to whether or not there presence in an area contribute to improving labour outcomes in that area. Data limitation among others is a key factor hindering any such analysis. Similar to Chauvet et al. (2015), we start this analysis first by compiling a list of all such registered CBO's in France.

This paper joins a growing literature on the effects of social and informal networks on

 $^{^1 \}mathrm{See}$ Cordero-Guzmán (2005) for a description of similar CBO's found in New York city, U.S.

²See Portes et al. (2007)

immigrants labour market outcomes by focusing on the effects of such CBO's in the economic integration of immigrants using North African (Maghreb) immigrants in France as a case study. The study focuses on three measures of economic integration; labour force participation rates, employment rates and job quality measured by earnings. I use data from the French labour Force Survey (FLFS) for the period between 1990 and 2012 and an original data collected from the French official journal and conducts the analysis at departmental level. I rely on a tripledifference strategy to compare individual outcomes between departments where this CBO's are present and in departments where they are absent both before and after they are targeted by a CBO. In the absence of information on immigrants beneficiary status from such CBO's, the paper define treatment using an indicator variable for the presence or absence of a CBO to mitigate the problems of measurement error. The study first estimates a simple probit model with labour force participation as the dependent variable, then I use a probit model to estimate the probability of being employed conditional on participating in the labour force. The paper later on controls for the endogenity in the location decision of immigrants by instrumenting the distribution of the current stock of the immigrant population with the distribution of the population in the past. Finally, it investigates its effect on earnings.

However, since migrants and social networks are not randomly selected, simply comparing outcomes of treated and control groups would likely yield a biased estimate of the causal effect of this CBO's. This is because characteristics associated with a given department or migrants which may be strongly related with the presence of CBO's may be driving the labour market outcomes of immigrants rather than the presence of a CBO itself. I first try to account for this by controlling for department and time fixed effects in all specifications. Then to tackle the problem of selection bias, I use the Propensity score matching technique due to difficulty in obtaining a suitable instrument.

The main findings of this paper are as follows; labour force participation and employment rates differs significantly between native french and Maghreb immigrants. Maghreb immigrants are less likely to participate in the labour force as well as to be employed. The presence of an association in a department have a positive and significant effect only on the labour force participation rates and employment rates of Maghreb women. Though the estimated effect for men is positive, it is not statistically significant. This effect is robust to controlling for both cohort and network effects. The study also finds that similar to other studies, immigrants cohort of arrival, length of stay, education and age all have a positive and significant effect on labour market prospects of immigrants. On the other hand, it finds that the presence of large co-ethnics in a department has an opposing effect for men and women. Whilst it benefits women, the reverse is the case for men. The paper does not find any evidence that the increase in employment is associated with lower earnings.

This study further finds that young Maghreb women and newly arrive immigrants are the

one's who benefits disproportionately more from the presence of this institution. This could be due to several reasons, a notable one is the fact that this group have poor initial conditions and thus makes it easier to improve there labour outcomes. Like in many developing countries, the labour market in Maghreb countries are not well developed and does not require complex bureaucratic procedures to obtain a job. This is particularly the case for these migrants and is evident by looking at the educational attainment of these migrants. Hence institutions that provide such services could prove quite instrumental in improving labour market prospects of this group. Another reason is that, the reasons for immigration of this group especially for women is mostly non-economic and hence are less prepared for the labour market as such the services provided by CBO's could prove quite instrumental.

This paper mainly contribute to two existing strands of literature. First it contributes to the literature on the role of social networks and social capital. It highlights how undirected government policy could have some unintended benefits for an ethnic minority. The Maghreb immigrants and other immigrants in France have exploited the implementation of a law to organise themselves into groups and address relevant issues affecting them. Similar to Borjas (2003), this study also highlights the role of semi-formal institutions in improving labour market outcomes of an ethnic minority in an imperfect labour market. Secondly, this paper contributes to growing debate both among scholars and policy makers on how to integrate immigrants successfully in the labour market of host countries. This study highlights a potential channel that if exploited could significantly help in this process. The biggest strength of this CBO's lies in their proximity to the immigrants. With proper support and collaboration with local authorities, these institutions could help harness the gains from migration.

The rest of the paper is organise in the following way; the next section, section II provides a brief review of the literature, section III provides a brief background of Maghreb migration to France and a description of registered migrant CBO's. Section IV outlines the data sources and provides some summary statistics, section V highlights the proposed methodology whilst section VI reports the baseline results, section VII investigates the mechanisms involved and carry out a robustness check of our results before concluding the paper.

1.2 Literature Review

This paper is closely related to three main strands of literature, first is the literature on the cultural and economic integration of immigrants, secondly is the literature on social networks and social capital and thirdly the emergence and roles of migrant associations.

The cultural integration patterns of immigrants have been mainly studied by sociologists. For instance, Algan et al in Cul (2012) provides an overview of cultural integration in Europe. The authors highlight a positive level of cultural integration mostly for the second generation immigrants in France, Italy, Germany Spain, UK and the EU as a whole. However, for the first generation immigrants significant differences exists in terms of fertility rates, marital age, inter-ethnic marriages, age completed full time education among other indicators. On the other hand, economist have been mainly interested in the economic assimilation of immigrants, there impact on the labor market, fiscal effects and provision of public goods. Economic assimilation has been mainly defined as the rate of convergence in labor outcomes of immigrants and natives such as earnings (Chiswick (1978), Borjas (1994)). A pioneering contribution to the study on the economic assimilation of immigrants in the US was by Chiswick (1978). Conducting a cross-sectional analysis, Chiswick find that immigrants initially earn less than natives but that immigrants earning increase significantly at a rapid rate with schooling and experience acquired in the US to the extent that their earnings catch-up with natives and even exceeds it after significant years of labor market experience in the US. This study was followed by several others including Borjas (1985) Borjas (1992) Borjas (1994). Algan et al. (2010b), carried out a comparative study of the economic situation of first and second generation immigrants residing in France, Germany and the United kingdom, conducting separate analysis for men and women. The authors find that, first-generation immigrants regardless of gender earn significantly less than natives. The earning gap is found to be relatively smaller in France and Germany among first-generation immigrants and to be significantly larger in the UK. For employment outcomes, first-generation immigrants in all three countries with the exception of Southern Europeans and Northern Europeans in France, and EU 16 immigrants in Germany, immigrants are less likely to be employed than natives.

In recent years economist have also recognized the important roles of non-market social interactions in the socio-economic integration of immigrants. Previous scholarly work on this literature have highlighted the important role of social connections and social networks in improving labour market outcomes, particularly for immigrants and other ethnic minorities³ Borjas (1992) and Chiswick and Miller (2002b).⁴ It has also been identified that the popularity in the use of these networks stems from the fact that they help to mitigate the problems of

³See Putnam's work on this literature for a broader discussions on the concept of social capital.

 $^{^{4}}$ Montgomery (1991), provides a summary of some relevant findings on how friends, relatives and people from the same origin communities provide referrals to potential job seekers and the reason for the use of this networks by employers.

informational asymmetries and improve the matching process between potential employees and employers primarily through their refereeing role that serves as screening device (Montgomery (1991) and Munshi (2003)).

The size of the immigrant or ethnic population from the same origin community residing in the same area has been the main measure of social networks used in the literature (Borjas (1992), Chiswick and Miller (2002b) and Munshi (2003)). Other variations of the measure of social network is the number of family members, relatives and friends residing in the same origin or destination area (Amuedo-Dorantes and Mundra (2007)). One of few exception to this is the use of migrant smugglers known as "Coyotes" as the main measure of migrant or social networks (Dolfin and Genicot (2010)). Earlier works on the topic provides both the theoretical and empirical foundation needed for further research. For instance, Montgomery (1991), developed an adverse selection model that attempt to explain the role of connections in improving labor market outcomes for individuals and profits for hiring firms through referrals from older or more established employees. He shows a possible mechanism in which social structure can be incorporated in economic analysis.

Similarly, previous empirical work has also address the topic in various dimensions ⁵. The findings from these studies have mainly been uniform. Borjas (1992), finds that ethnic capital and parental education have a positive and significant effect on the earnings, educational and occupational attainment of offspring's of immigrants. likewise, Similar effects were found for inter-generational mobility, the effect being higher for offspring's of first generation immigrants. Others generally find that the networks significantly improve the likelihood of employment of its members and benefits the most those that would have been more disadvantaged such as women, older men and the less educated in the absence of this networks. Furthermore, some studies also find that these networks also helps in channelling its members to higher paying non-agricultural jobs through its more established members by means of referrals (Munshi (2003), Amuedo-Dorantes and Mundra (2007)). Chiswick and Miller (2002a), finds that individuals with a higher human capital and whose skills are easily transferable tend to have jobs with a higher occupational status. However, individuals with a higher job status previously experienced a greater loss in occupational status in their first job. Similarly, Borjas (2015) also find that immigrants earnings improve with the time spent in the destination country. This is because overtime migrants acquire country specific skills such as fluency in the language for migrants arriving in the U.S.

These studies provide evidence on the existence and role of social networks in modern economies and how this could be incorporated in the economic analysis on the integration

⁵Most of the previous studies on the topic has mainly focus on Mexican immigrants in the U.S (Munshi (2003), Amuedo-Dorantes and Mundra (2007) and Dolfin and Genicot (2010)) mainly due to the availability of data, the magnitude of the migration and the nature of its migration pattern. Among the few exceptions to this include Chiswick and Miller (2002a) who focused on immigrants arriving in Australia. (Menjivar 2000) on Salvadoran immigrants and (Nee 1997) on Chinese immigrants

process of immigrants and other ethnic minorities. These studies also highlights the important role of policies targeting integration of current immigrants on the labor outcomes of subsequent generations (Borjas (1992)).

Another literature that has been attracting increasing attention from both sociologist and economist is the literature on the emergence of migrant associations in host countries and the roles they play in both origin and host countries. Some like Home Town Associations⁶ have mainly focused on the local development of their origin communities through the provision of public goods such as building schools, hospitals, increasing access to water and electricity, supporting candidates to oust dictators. For instance Chauvet et al. (2015) finds that Malian villages targeted by migrant associations located in France have a significantly lager number of public goods as compared to their counterparts that are not targeted by migrant associations. Similarly, Beauchemin and Schoumaker (2005) in a study on the impact of migrant associations on local development for villages in Burkina Faso find that being targeted by migrant associations located in Ivory coast was a crucial tool for having a primary school, a health center and all season road. Kijima and Gonzalez-Ramirez (2012) finds evidence that Mexican communities that access the 3x1 program⁷ were better-off than there counterparts without the program mainly through improvement in basic infrastructure such as roads, water supply and non-agricultural productive projects even though its effect was modest.

Another form of migrant association which is the main focus of this paper are those engaged in the economic integration of immigrants in their host countries. Migrant associations engage in integration like Home Town Associations (HTA) are voluntary associations established by immigrants in host countries mostly gathering immigrants from the same origin country with the main aim of improving their labor market outcomes in the host country. So far, very little studies have systematically investigated its impact. Few exceptions include, Bosiakoh (2011) who studied the Nigerian immigrants associations in Ghana, highlighting the reasons behind its formation and their role in improving living standards of this immigrants.

However, unlike the attention receive by HTA's, associations engage in the economic integration of immigrants have received little scholarly interest. There are no empirical studies that have systematically investigated the effect of this associations on labour outcomes of immigrants. This paper uses an original data-set of such associations registered in France by Maghreb immigrants to investigate its effects on the economic integration levels of Maghreb migrants residing in France. We mainly focus on labor force participation, employment and to some extent earnings.

This study contributes to the existing literature in the following ways, First, it extends the

 $^{^{6}}$ Rouse (2007) Manuel Orzocco is a leading researcher in the field, see Manuel Orzocco and Rebecca Rose https://www.migrationpolicy.org/article/migrant-hometown-associations-and-opportunities-development-global-perspective

 $^{^{7}}$ A program in which contributions by migrants are matched by contributions from the federal, state and county governments with the main aim of carrying out public works or projects

literature on social networks by analyzing the effect of the formalization of immigrants social networks through the formation of associations or evolution of institutions specifically aimed at improving labor market outcomes of immigrants. Secondly, this paper contributes to growing debate both among scholars and policy makers on how to integrate immigrants successfully in the labor market of host countries. It identifies another complementary channel to the exiting ones which if utilized could facilitate the process of integration. Thirdly, it highlights the role of public policy in improving "social capital" that may have both direct and indirect effects on labor markets. Finally, this studies focuses exclusively on the gap between Maghreb immigrants and French natives. To the best of my knowledge, this is the first study attempting to provide a systematic analysis of the effect of this association on the labor market integration of Maghreb immigrants, the largest non-European immigrants in France.

1.3 Background and context

Migration from the Maghreb to France is an old one. This could be trace as far back as the colonial era. These colonial links to date constitute a major determinant of migration from north Africa to Europe. Each of the three countries studied here gained its independence from France in the 1950's, starting with Morocco and Tunisia in 1956 and Algeria in 1962. The first wave of North African migration to France was mainly related to the world wars in which many North Africans fought alongside the French army. The second wave was mostly related to recruitment of workers during the post war periods to rebuild the country and provide labour for the emerging industries (Haas (2007)). They mainly serve to fill the gap left by the two world wars. During this period the governments of these countries signed bilateral agreements to ease the movement of workers to France and other European countries. This continued up until the period of the global oil crises in the 1970's during which the French government ended the agreement. However, during this period, the generous French policies on family unification led to a large number of immigrant arrivals mainly composed of women and children. This also discouraged return migration and prompted permanent settlements and "over stayers" (Haas (2007)). Since then, France have imposed more restrictive policies on immigration.

Maghreb migrants are the largest share of immigrants in France originating from non-EU countries. As at end 2015, they constitute about 30 percent of the total immigrant population the second highest after other EU migrants.

In terms of the location of this immigrants in France they are mainly concentrated in the large urban areas relative to natives and other EU immigrants. For instance over 90 percent of immigrants from Algeria and Tunisia live in large urban areas as at 2012 out of which half live in the industrial regions in France, Ile-de-France, Lyon, Marseille and Grenoble. Whilst Moroccans on the other hand were not only restricted in the large urban centres, but they could also be found in smaller and medium-size municipalities. About 56 percent of immigrants from Algeria resided in the departments of Seint-Denis, Paris, and Val-de-Marne. Whilst Moroccan's were a little more widespread about 50 percent lived in Paris, Montpellier, Avignon, Lille, Lyon, Toulouse and Marseille⁸. Their selective concentration or location has allowed the replica of their traditional structures similar to those in their origin countries and the emergence of other forms of associations mainly geared towards serving their collective interest. Among this organisation's are CBO's which have evolved overtime with the aims to promote the integration of its immigrants. Their formation, objective and mode of operation are outlined in the subsequent section.

Description of registered migrant associations

This section provides a brief description of migrant associations⁹ outlining the reasons behind their formation, the nature of their activities, their potential role in the integration process, how and why are they different and the potential channel through which they may influence immigrants outcomes. I try to define some concepts and propose answers to some questions in relations to how they are used in the paper.

The role of CBO's and other civil society organisations on the integration process of newly arrived migrants cannot be overemphasised as recognised by the High council for integration (Haut conseil pour l'integration (HEC)), and as highlighted in the INTERACT research report 2015. Their close proximity to migrants is of great importance in understanding the challenges faced by individuals and devising solutions to this problems. However, as highlighted in the literature, due to the nature of their formation and operation coupled with the paucity of data, the quantification of their effects is a very challenging task. Nonetheless, I attempt to provide some insights about this institution by exploiting the limited available data.

• What are migrant local economic associations? Migrant local economic associations also known as CBO's are voluntary organisation's aimed at improving the welfare of immigrants in the labour market and aim at maximising the gains from migration (See Cordero-Guzmán (2005) for a description of similar CBO's found in New York city, U.S.). They are engage in the economic integration of immigrants through the provision of assistance to either specific migrants from the founders origin country or to all migrants arriving in a specific place in the destination country. The aims, objectives, address and targeted group for this association are usually spelt out clearly in the document declaring registration¹⁰. This declaration is a necessity to be recognised as a formal body and a requirement for other necessary documentation for instance to open a bank account in

 $^{^{8}}$ Chantal Brutel, statistics and immigration studies INSEE. 2012 provides a descriptive analysis of the geographic locations of immigrants in France

 $^{^{9}}$ The terms migrant associations, migrant local economic associations and associations for integration's are use here interchangeably to refer to the same thing unless otherwise specified.

 $^{^{10}}$ see an extracted snapshot of the document declaring registration.

which the funds of the association could be kept ¹¹. The formalisation of a network in this case the registering of a migrant association is an indication of the extent of commitment by its individual members to gain recognition and to attract the support and commitment of others in achieving the associations goals.

- How and why are they formed? They could be formed by individuals from the same origin community or by any group of people being it immigrants or not or any civil society group (Cordero-Guzmán (2005)). For instance, Bosiakoh (2011) outlined that the timing of the formation of this associations are influenced by the migratory nature of individuals. For Moroccans in France, it was due to the leftist repression of the opposition as a result most of their earlier organization's were mainly political in nature geared towards supporting the opposition in Morocco. However, the unfavourable labour market conditions faced by this immigrants in their host country led to the creation of a new association to help in tackling this issues (Lacroix (2011a), Dumont (2012)).¹² ?, highlighted a reduction in support provided by unions to immigrant workers in France as one of the reasons for a large increase in immigrant associations. Immigrant associations provided practical assistance to immigrants applying to regularize their status during the 1997 1998 regularization program instituted by the Jospin government. Immigrant associations mainly stepped in as a substitute when labour unions failed to play an active role in aiding this process as they have done in 1981-1982.
- How do they help in the integration of new migrants? The role of this associations as highlighted earlier may depend greatly in the factors motivating its formation and in general this ranges from helping to secure housing or accommodation needs, financial assistance in the form of soft loans, help in the cultural integration and break language barriers through language training classes, easing adjustment difficulties, fight against discrimination and xenophobia, CV preparation, helping immigrants acquire the necessary documentation and to some extent serve as an advocate for better pay and working conditions for immigrants ¹³. For instance Tunisian migrant association are also known to advocate for the recognition of foreign diplomas earned by immigrants in their origin countries in the host countries. This could go a long way in improving labour market outcomes of immigrants. Lochmann et al. found evidence of an increase in labour force participation rates for individuals who benefited from language training classes organised the French interior ministry.

 $^{^{11}}$ Other forms of this association exist for instance those promoting Tourism, Human rights, Socio-cultural activities and so on. However we limit ourselves to those engage in integration as it is the main concern of the paper

¹²" Association des Travailleurs Marocains de France (ATMF)". This name was later to change to admit other Maghreb non-Moroccan nationals hence the name "Association des Travailleurs Maghrébins de France" Lacroix and Dumont (2012), Dumont (2012)

 $^{^{13}\}mathrm{In}$ this case there activities could be seen similar to the activities of labour unions.

In terms of Financial capability, Lacroix (2011b), from a survey of twenty eight different forms of Moroccan organisations registered in France, found that over forty percent had an annual budget of over ten thousand euros. however, as they highlighted "low budget" does not necessarily mean "small and local". Citing the fact that aside from their internal resource generation which is mainly through individual contributions and other fund raising activities, they may be beneficiaries of grants from other Non Governmental Organisations or may participate in coordinating projects involving large financial flows. With regards to the composition of its board members, he found majority of the boards to be composed of individuals with a university degree and people of mixed origin¹⁴, Moroccans and French origin. This is geared towards increasing the support base for the association. They also find that most members and supporters resided in the same area. though this could extend to a wider geographical area. Hector et al (forthcoming) cited the role played by this organisations in bringing the issue of immigrant integration in the lime light and their efforts in involving authorities and the role they played in crafting the Spanish Integration model. He also find that most of this associations benefited largely from both origin and host countries support to implement projects related to migrants in either side of the shores.

However, one should be mindful of their potential adverse effect in the integration process. leaving in an "ethnic enclave" does not give much incentive to individuals particularly those arriving newly to want to acquire skills relevant for integration in the host country such as language training or other cultural traits. If anything this may go against the intended purpose of this associations.

• But how are they different? One may argue that using this measure of social network is more or less the same as previous measures such as using the size of the migrant population, the number of family members in the destination country or the number of relatives and friends. However, I will like to stress the following crucial distinctions; first, this associations have a legal identity and a formal structure. As such they are better able to mobilise resources from individuals, local government institutions and non-governmental organisations to implement their activities (Hector et al (forthcoming))¹⁵. Their formalised social structure, gives them a strong bargaining power to lobby as a group on behalf of its membership and are more likely to get support from local and external organisations to fund their activities. Secondly, in areas where the information on the labour market is imperfect, they could potentially serve to reduce this asymmetry by serving as points of contact and intermediaries between potential employees and em-

¹⁴Cuaresma et al. (2015) also find similar characteristics for CBO's in the New York,

 $^{^{15}}$ It is even suggested that they played a significant role in the 2017 elections in France by encouraging people to vote against the anti-immigrant government. They have also be known to be the organisers of large protest in the Banlieus

ployers¹⁶. In addition they help to expand the migrants network rather than restricting it to only family and friends. Most importantly, their proximity to the immigrants give them a better understanding of the problem in hand and hence are in a better position to propose solutions to this problems and help direct the efforts of other state and non-state actors.

1.4 Data and Descriptive statistics

The analysis will mainly be carried out at the second finest geographical level; departments, mainly due to availability of comparable data. This paper will rely on data from two main sources. We use micro level data on individuals demographic characteristics and labor market outcomes from the French labour force Survey (FLFS) conducted by the French National Institute for statistics and Economic Studies (INSEE) ¹⁷. Information on migrant associations engage in aiding the integration of immigrants is derived from the register of the french official journal ¹⁸.

The micro level data from the FLFS comes from two distinct waves. The first wave (1990 to 2002) collected annually consists of a random sample of about 145,000 persons per year, sampling rate of 0.35 percent. The second wave (2003 to 2012) collected quarterly covers a random sample of about 290,000 persons per year with a sampling rate of about 0.65 percent. The FLFS provides detail data at the individual level on natives and immigrants demographic, social and labour market characteristics. Similar to Edo and Toubal (2015), we will use an individual weight provided by INSEE to make our sample representative of the french population. We collapse the quarterly data from the second wave to obtain an annual data. The association loi 1901 which came into effect when the french socialist government took over in 1981 allows any citizen above the age of 16 years to associate freely, without prior authorisation. Newly established associations are required to declare themselves by providing information about their aims and objectives, activities and address of their registered office. The Journal contains data on registered association from 1981 to date. However, for the purpose of this analysis we restrict ourselves to those registered between 1996 (the first year in which information is available) and 2012.¹⁹ For a discussion on the methodology of this data collection and its potential weakness refer to Chauvet et al. (2015).

We restrict our analysis to only persons located in mainland metropolitan France. Following previous studies in the literature (see Chauvet et al. (2015), Borjas (2003), Munshi (2003)), we restrict our analysis to only individuals in the working age group, that is those aged between 16 and 64. Similar to Borjas (2003) and Edo and Toubal (2015), we define immigrant status

¹⁶See Montgomery (1991)

 $^{^{17}}$ Institute National de la statistique et des Etudes Economique

¹⁸http://www.journal-officiel.gouv.fr/

¹⁹In 2013 and 2014, data on individuals country of birth was not collected, hence to avoid this gap in our data we restrict the sample to 2012.

based on place of birth, as such our immigrant population consist of any individual residing in France that was born in either of the three Maghreb countries regardless of his current nationality status.²⁰

Descriptive statistics

Figure 1.2 shows the evolution of the Maghreb population in France overtime as a share of the total foreign population between 1968 to 2015 using census data ²¹. We could see that this share as at 1968 was about 8 percent and by the end of 1990 it has significantly increased to about 22 percent though this proportion fell by the end of the 20th century it was quick to pick up and have since registered a stable growth averaging about 26 percent of the total foreigners in France as at end of 2015, second only to immigrants from the EU mainly from Italy, Spain and Portugal.

Education

The FLFS provides information on educational attainment based on the International standard classification of Education (ISCE) ranking. These are originally grouped into six categories and a baseline group for individuals with no education. We broadly regroup this into four main categories, individuals with only a middle school qualification or less were classified as having only a basic education, those with different high school diplomas were classified as possessing a high school qualification, individuals with different specializations of various undergraduate degrees and professional qualifications were classified as having a first level tertiary education and those with higher level tertiary education such as masters and doctorate degree were categorized as having a postgraduate degree.

Table [1.6] shows the percentage of the population with different educational qualifications in the years 1990 and 2012. The table reveals that on average there has been an increase in the percentage of both immigrants and natives with higher educational qualifications between 1990 and 2012. Table [1.7] Provides the percentage of natives and immigrants in our data with different educational qualifications grouped according to gender²². This results were adjusted using the sample weight of each individual in the population²³. The results show a great disparity across immigrant status than across gender. We find that on average natives have a higher level of educational attainment compared to immigrants in all categories except for the highest level of educational qualification, that is those holding a graduate degree.

 $^{^{20}}$ Note: we use the term here Maghreb immigrants and Immigrants interchangeably to refer to immigrants from the three main Maghreb countries, Algeria, Tunisia and Morocco unless otherwise specified.

 $^{^{21}}$ Note: The census data only provides information on nationality and not immigrant status, hence this could be seen as a lower bound for the Maghreb population as it excludes immigrants who have obtained french nationality.

 $^{^{22}}$ Note: this calculations are done for individuals in the working age group which include all those currently classified as students, hence the higher proportion of those with only a basic education.

²³EXTRI

We find that for natives about half of its population have at least a post high school qualification whereas for immigrants about 50 percent have only a basic education or less. However, when we look at only the top or highest educational qualification, that is those with a graduate degree we find a slightly higher proportion of male immigrants in this category relative to native males. The reason for this may be partly explained by the fact that most immigrants from former french colonies including those from the Maghreb travel to France to pursue higher education and eventually decides to stay and work in France.

Labor Force participation

Looking at labor market participation, we use the individual reported activity in the labor market according to the definition adopted by the international labor organization to classify individuals as either employed, unemployed or inactive in the labor market. Table [1.8] shows the evolution of employment outcomes for the years 1990 and 2012. We observe a significant increase in labor force participation for both native and Maghreb women and a mild increase for native men whilst for Maghreb men we observe a slight decrease. Similarly we observe a significant increase in employment rates for women whilst for men employment rates fell by a small margin. Table [1.9] above provides a summary of the data. The results show disparity in labor force participation rates both across genders and across immigrant status. Female natives have almost 20 percent higher participation rates in the labor force than female immigrants. This could partly be attributed to the cultural and religious beliefs of the Maghreb immigrants who mostly relegate their women to household chores and taking care of the family. With regards to males, labor force participation rates of immigrants and natives are almost equal. However, in terms of those who are actually employed, natives have a higher employment rate relative to immigrants (with a margin of about 8 percentage points) and the unemployment rates of immigrants is about double that of natives.

Other Variables

The FLFS provides some additional individual-level data relevant in explaining labor market outcome, We provide a brief motivation for their inclusion and a description of how they are constructed. Factors affecting the marginal utility of work relative to leisure (which heavily depends on taste and preference of individuals) and the general economic condition of the area among other things are known to influence individuals decision to participate in the labor force. The economic conditions such as the probability of obtaining a job, the wage rate, welfare regimes, working conditions, industrial structure of the area are significant ingredients in the labor force participation decision making process.

Similarly, previous studies in the literature find that individual characteristics like the age of the individual, the marital status, the presence of children and or the elderly in a household, immigrant status and education level to affect labour force participation rates (see Borjas (2015))). Borjas (2003) finds that immigrants year of arrival in the US have a differential effect on both earnings and growth rates of earnings with recent immigrants earning lower and having a lower growth rate of earnings. We construct a categorical variable for cohort of arrival divided into 8 groups to capture this cohort effects. Using information on the migrants first year of arrival, we compute the length of stay as the difference between the year of the survey and the immigrants year of arrival in France.²⁴ We also control for wave specific effects that may be related to the data collection of each wave.

labor market experience as highlighted by (Chiswick (1978), Borjas (2015)) is an important determinant of labor market outcome. Though there is much debate empirically about how to account for the differences in return to labour market experience acquired before and after migration²⁵, we follow chiswick's approach and impose the assumption that the returns between the two are not very different. Following Edo and Toubal (2015), potential labor market experience is computed as the difference between individuals current age and age at which the individual completed full-time education. whilst for individuals whose school completion age is less than 12 this figure is scaled up to 12 since individuals are very unlikely to participate in the labor market before such an age. we also re-coded age into 8 categories, this is motivated by the possible competition and substitution effect that might happen at the skill-cell level.

Gender, marital status and fertility are also known to influence the decision on labor market activity. This variables and sometimes their interaction have been used to control for the selection decision into labor force participation.²⁶ Changes in Marital status and fertility measured by number of children most often translates to increase incentive to look for employment for men whilst it is negatively associated with labor force participation for females (see Heckman (1979)). This factors will even be more important for our study sample. Maghreb immigrants due to their strong religious beliefs and cultural practices have the tendency to be very conservative about female employment.

Furthermore, educational attainment and labor outcomes are known to differ substantially between the different genders as we have seen in the descriptive statistics earlier. It is also a well known fact that immigrants have a high tendency to locate in highly urbanized areas relative to natives and that labor market returns might differ in this two areas particularly for the two groups, we include a dummy variable to control for this effects.

Table [1.11] provides a brief summary statistics of some of our variables in the sample. Immigrants make up about 5 percent of our sample. The average age of an individual in our

 $^{^{24}}$ Since the nature of this group of immigrants with regards to time spent at home country is mostly for vacation and short family visit in addition to the fact that after the first visit they are likely to be familiar with the cultures and can establish ties with others, we believe this will accurately capture their social capital from residing in France.

 $^{^{25}}$ for instance Chiswick (1978) did not find much difference between return to experience in the origin country and destination country likewise the interaction of the two

 $^{^{26}}$ see Heckman (1979) for a pioneering work on selection models that uses this variables to control for the selection decision.

sample is 42 years with almost equal proportion of males and females. On average about 56 percent of the people in our sample are married and over 72 percent are cohabiting with a partner. The average household are composed of about 3 people with Over 60 percent of the population living in urban areas and about 14 percent living in Paris. The average years of experience is 21.

Migrant Associations

The following section provides some descriptive analysis on registered migrant associations. The data on the establishment of associations from the french officiel journal is summarized below²⁷.

Targeted Immigrants	Algeria	Morocco	Tunisia
1997	6	4	1
2002	47	27	12
2012	30	78	28
Total	83	109	41

The first table above shows the number of associations that were newly registered within each period. We observe that only a small number of associations were registered by the end of 1997. A significant number of association were registered between 1997 and the year 2012. A total of about 233 were registered in all.

Targeted Immigrants	Algeria	Morocco	Tunisia	Maghreb
1997	6	4	1	10
2002	28	16	8	38
2012	34	35	18	54

The second table above shows the number of french departments where migrant association engage in the integration of migrants are present. By the end of 1997, about only 10 out of the 96 french departments considered here have had at least one migrant association registered in it. This number increased significantly to about 38 departments by the end of 2002. This increase slightly to about 54 departments accounting for about 56 percent of all french departments in metropolitan France by the end of 2012.

Despite the significant increase in the number of newly registered migrant associations, the number of departments where an association was established for the first time did not increase that much. For instance for the case of Algeria despite the significant increase of about 30 new associations between 2002 and 2012, only 7 departments were targeted for the first time.

²⁷Note that we were very careful in classifying an association as one that is engaged in the integration of Maghreb immigrants, only association that clearly state in an unambiguous manner that there purpose is to help provide integration assistance to Immigrants from its origin country. Hence, whatever results produce from using this list should be seen as conservative.

This is in part explained by the fact that majority of the new registration where an association already exist was observed in the metropolitan city of Paris, the largest department in France. Another explanation might be to extend the associations to other parts of the department that are distant to the places where the existing ones are operating and to probably replace old ones that are dying out or to complement their efforts.

1.4.1 Measurement error

There are sufficient reasons to believe that our data on migrant associations is not exhaustive due to the fact that not all associations might be registered or the possibility that some of the associations listed on the journal are no more existing. Hence the problem of measurement error.

As a way to mitigate this problem, we propose to use an indicator for the presence or absence of an association in a department rather than the total number of registered associations. That is, a departments is define as being treated if at least one association is registered in that department. the year of treatment beginning from the year in which the first of such association was registered and remains as treated for the rest of the subsequent years. On the other hand departments are defined as being in the control group if no association was registered in the department throughout the period under study. ²⁸. For example if in the department of Ain, the first association was registered in 2004, we label Ain as a treated department from year 2004 and throughout the period regardless of whether another association was registered or not. On the other hand departments in the control group consist of two types, first those that were not treated in the beginning of the study and subsequently became treated and those that were not treated throughout the study. In the example above, the department of Ain will be in the control group for all periods prior to 2004 and in the treated group afterwards.

Preliminary evidence

As a first step we investigate if there exists any statistically significant unconditional differences in outcomes of immigrants and natives in departments where an association is present and in areas where it is absent. Carrying out the investigation across gender is necessary noting the differences in labor participation rates for male and female immigrants and differences in the occupational composition of this two groups. Traditionally female Maghreb immigrants mainly serve the role of house wife due to their conservative culture and religious belief which partly explains the low levels of labor force participation rates observe among Maghreb women relative to natives. We mainly investigate differences in terms of average labor outcomes such as share of persons employed, unemployed and inactive as well as educational attainment.

 $^{^{28}}$ A similar approach was used by Chauvet et al. (2015) who used a similar dataset to study the effect of Hometown associations on local development.

Table [1.12] shows that the unconditional outcomes for both native females in treated and control departments are very similar. For female immigrants, a slight difference of about 4 percentage points is observed. However, for native men we find the contrary. Employment rates of immigrant men in treatment and control group are almost equal, whilst for native men we observe a lower employment rate in the treatment group. For both natives and immigrants, we observe a slightly higher unemployment rate in the treatment group. However, we see a lower inactivity rate for immigrants in the treatment group compared to natives. between treated and control departments. This may serves as suggestive evidence on the existence of differences in labor outcomes between treated and control departments.

Table [1.13] shows that there is differences in educational attainment between treated and control departments as well as between natives and immigrants. Those in treated departments possessing relatively higher educational qualifications.

1.5 Analytical framework

One way to estimate the effect of CBO's on labour outcomes of Maghreb immigrants is to restrict attention to only departments where a CBO is present. Then compare changes in labour outcomes of Maghreb immigrants using natives as a control group. However, a potential problem to this approach is that, other factors unrelated to the treatment might affect labour outcomes of immigrants relative to natives. For example, changes in immigration policies at the national level. An alternative approach could be to use immigrants in other departments as the control group. Here, the problem will be, changes in labour outcomes might be systematically different across departments. For example, due to difference's in educational attainment for people residing in the two departments rather than the presence of a CBO.

Therefore, we use a more robust approach that involves using both other departments and natives within the treated department as control groups. With this approach, we hope to control for two types of confounders. Firstly, changes in labour outcomes of immigrants across departments that have nothing to do with a CBOs. Secondly, changes in labour outcomes of all people living in departments where new CBOs are registered. Possibly due to other department policies affecting everyone's labour outcome, or department specific changes in the economy that affect everyone's labour outcome.

1.5.1 Empirical Framework

The empirical analysis proceed as follows; first, by carrying out the analyses separately for males and females, the paper estimates the initial labour market conditions for newly arrived immigrants with demographic characteristics and skills comparable to natives. Using the presence of a CBO as a measure of integration allows comparison of changes in the labour outcome gap between new immigrants and natives in treated and control departments. Second, the paper controls for cohort effects to allow for the native-Maghreb labour outcome gap to vary across cohorts arriving at different times. Thirdly, noting the important role of networks in improving labour outcomes of immigrants, the paper controls for the stock of Maghreb immigrants residing in each department to capture this network effect.

The empirical investigation begins by adapting the established empirical approach on immigrants earning assimilation used in the labour economics literature (see Chiswick (1978), Borjas (1985), Borjas (1995) andBorjas (2015)) to study the role of voluntary CBO's on labour market integration of immigrants. The paper specifically modify the dependent variable to explain the probability of participating in the labour force and the probability of being employed. Then it introduces a variable to capture the effect of the presence of a CBO in a department on the labour outcomes of Maghreb immigrants residing in that department.

labour Force Participation

Focusing on labour force participation, the following basic specification is proposed;

$$LF_{i,d,t} = \begin{cases} 1 & \text{if } Y_{i,d,t} > 0 \\ 0 & \text{if } Y_{i,d,t} \le 0 \end{cases}$$
(1.1)

An immigrant i participates in the labour force (LF=1) only if the latent variable $Y_{i,d,t} > 0$ with the latent variable specified as follows:

$$Y_{i,d,t} = X_{i,d,t}\beta + \epsilon_{i,d,t}, \epsilon \sim N(0,1)$$
(1.2)

which means that the probability of participating in the labour force is

$$Pr(LF = 1) = \Phi(x'\beta) \tag{1.3}$$

were ϕ is the probability distribution function of a standard normal random variable. We assume $Y_{i,d,t}$ to be a linear function of the following form

$$Y_{i,d,t} = \gamma + \beta_1 A_{d,t} + \beta_2 I_{i,d,t} + \beta_3 A_{d,t} I_{i,d,t} + \phi_i X_{i,d,t} + \lambda_d + \tau_t + \epsilon_{i,d,t}$$
(1.4)

Where the dependent variable is a dummy for activity status in the labour market. labour force participation equals 1 if the individual is active in the labour market, that is either employed or unemployed and equals 0 otherwise. The subscripts i, d and t refers to individual, department and time respectively. The model includes an indicator variables for treatment status (A) which is equal to 1 if a department has a CBO present from the year of first registration, an indicator variable for immigrant status (I) and an interaction of the two variables (A*I) to allows us estimate the relative differences in labour market outcomes of immigrants between treated and control departments.

The treatment status is assigned to each observation in the following way; the study begins by first identifying the date of first registration of an a CBO in each department. Individuals are then coded as being covered by a CBO if they are immigrants born in any of the three Maghreb countries and residing in a department where a CBO is present. A caveat, however, is that the data does not allow for estimating the effect on individuals who actually seek for assistance from this CBO's.²⁹

Individuals labour force participation decisions are influenced by both individual demographic and household characteristics. The variables controlled for includes: categorical vari-

 $^{^{29}}$ A probit model is not used to estimate model [1.4] due to the difficulty in estimating the maximum likelihood in the presence of many fixed effects, rather a simple linear probability model is estimated.

ables for education, a factor variable for cohort divided into 8 groups with natives serving as the base group. This accounts for the wave of migration also known as the cohort effect, it captures the relative reward for migrants labour depending on cohort of arrival in the host country. Other individual characteristics accounted for are; gender, marital status, residential characteristics such as if he cohabits with his partner, if the individual resides in a rural or urban area, number of people residing in the household and number of children below the age of 18. To account for unobserved department specific characteristics and overall time varying characteristics that may affect labour outcomes such as local macroeconomic and labour market conditions, department fixed effects and time fixed effects are included.

All the analysis are conducted at the age-education cell level hence the coefficient on immigrant status is interpreted as the initial gap between a newly arrived young-immigrant and native with similar characteristics. The indicator variable for the presence of a CBO measures the average difference in labour force participation rates between departments where a CBO is present and in departments where it is absent. The double interaction term on the other hand measures the marginal effect of the presence of a CBO on the integration of new immigrants.

A priori, one would expect outcomes of immigrants in the labour market to be lower relative to those of natives, $\beta_2 < 0$. Though this gap should be falling overtime with increase in length of stay due to acquiring country specific skills. One would expect the presence of a CBO to fasten the pace at which this skills are acquired thus leading to better labour outcomes of new immigrants located in these departments. since this CBO's are targeted one would expect to find an effect if any only for the targeted group,

Employment

To estimate the effect of a CBO on the probability of being employed for new immigrants, we slightly modify our model in [1.4]. We replace our dependent variable with the probability of being employed conditional on participating in the labour force.

$$Pr(E|LF=1) = \Phi(x'\beta) \tag{1.5}$$

We also restrict our control variables to only those that affect the individuals probability of obtaining a job. In particular, our control variables are now limited to the following; individuals level of education, cohort of arrival, length of stay in the host country, age, gender, marital status and place of residence within a department³⁰.

Our coefficient have a similar interpretation as explained earlier for labour force participation. All our analysis are also carried at skill-cell level. For instance, the indicator for immigrant status measures the difference in probability of being employed for new immigrants

 $^{^{30}}$ See Chiswick (1978), Borjas (1985) and Borjas (2015) on the relevance of these variables in the job search process especially for immigrants.

with comparable natives. This is because we are controlling for the immigrants length of stay.

Earnings

In order to estimate if a CBO have any effect on wages, we first note that the sample of individuals who are active in the labour force is a non-randomly selected sample and the fact that we are using a non-experimental data raises the problem of unobserved heterogeneity and selection bias.

For instance individuals with higher ability, education or are more motivated are more likely to earn higher wages in the labour market hence also more likely to participate in the labour force and as such estimating the earning differentials without taking this into account may yield a bias estimate (see Heckman (1979)). This paper first re-examines the original double hurdle model proposed by Heckman (1979), and adapt it to measure the effect of the presence of a CBO on earnings of immigrants. The dependent variable is hourly earnings of an individual conditional on participating in the labour force. Since this variable is censored for individuals who are inactive in the labour market, a heckit model is required. For the Heckman model the wage equation can be written as follows :

$$Wage_{i,d,t} = X_{i,d,t}\beta + \eta_{i,d,t} > 0 \tag{1.6}$$

and our selection equation as

$$z_{i,d,t}\gamma + \varepsilon_{i,d,t} > 0 \tag{1.7}$$

where $\eta \sim N(0,1), \varepsilon \sim N(0,1)$ and $\operatorname{corr}(\eta, \varepsilon) = \rho$. In equation [1.6], the earnings depends on a set of demographic and socioeconomic characteristics similar to those considered in the probit equation for employment. In equation [1.7], individuals are selected depending on whether or not they are active in the labour market. We estimate the two equations jointly to take account of the correlation between the error terms.

As noted in the literature, if we have the same variables in both x and z, our parameters of interest will be weakly identified as a result of the high level of collinearity between the two models due to the fact that identification comes from the same variables. In order to circumvent this, we apply an exclusion restriction to control for the selection decision, that is we use an instrument for z that is correlated with the labour force participation decision z but does not affect the employment outcome y except through its effect on z. We follow the norm in the literature for the variables determining selection into the labour force. Specifically we use an indicator for marital status, the number of people living in the household and the number of children below the ages of 18 residing in the household as our selection variables. To make sure our exclusion restriction is satisfied, two of the selection variables - size of the household and the number of children are excluded in the main regression. We apply Heckman (1979) twostep estimator which is more robust than the Full information Maximum Likelihood Estimator (FIMLE) for most practical applications.

1.6 Results

labour force participation:

Table [1.14] presents the results from estimating the baseline equation [1.4] using the full sample of natives and Maghreb immigrants distinguished by gender. The marginal effects of the probit estimates are presented in table [1.1]. The estimated coefficient on immigrant status is negative and statistically significant with its magnitude higher for females compared to male immigrants. This means that young Maghreb immigrants arriving newly in France have a lower probability of participating in the labour force relative to natives (about 11% for men and 26% for females) with comparable demographic characteristics and skills. The relatively lower participation rates of Maghreb women like other immigrant women can be attributed to cultural differences and low opportunities for women in the labour market of their origin countries. The main coefficient of interest measuring the role of a migrant CBO on integration is positive but not statistically significant for either genders. Though we do observe a relatively larger magnitude for women.

Another variable of interest is the length of stay in the destination country. Its estimated coefficient is positive and statistically significant whilst its squared term is negative and statistically significant. This means that the likelihood of participating in the labour force increases with the number of years spent in the destination country with its effect diminishing overtime. This suggests that the labour force participation gap between Maghreb immigrants and natives narrows over time as immigrants acquire some country specific characteristics. Its estimated effect for Maghreb men is relatively larger than that of Maghreb women suggesting a faster pace of integration for men than women. However, this effect is very marginal, it is less than 1% for every additional year spent in the destination country for both men and women.

Other control variables have the expected sign. The probability of participating in the labour force increases with the level of education. Highly educated individuals are more likely to participate in the labour market. Similarly, labour force participation increases with age though at a decreasing rate. Marital status, the presence of children in the household and the size of the household have a positive effect on the labour force participation of men and a negative effect for women. This results are consistent with the previous findings in the labour economics literature.
labour force participation and Cohort effects

Previous studies find evidence that the labour outcome of immigrants maybe dependent on their time of arrival in the host country. Failure to account for differences in migrants time of arrival at the destination may bias cross-sectional estimates if there are quality differentials in migrant cohorts (Borjas (2015)). For instance, if earlier migrants have higher labour outcome potentials than recent migrants, the estimated coefficient on the length of stay may overstate the true speed of integration. More importantly, our variable of interest, the presence of a CBO is a recent phenomena that is going to affect only migrants arriving from the late 1990's. Moreover, if we expect the effectiveness of this CBOs to increase overtime, excluding immigrants time of arrival is likely to understate the effect of this CBO's. We test for cohort effects by including the year of arrival in France coded into eight groups of eight years with natives serving as the excluded group. This allows us to observe the labour force participation gap between immigrants and natives across different arrival cohorts unlike in our basic specification were this was assumed to be the same.

column [2] of table [1.14] presents the results from including the cohort effects while the average marginal effects are reported in column [2] of table [1.1]. Interestingly, the coefficient for young and newly arrived immigrant status decreases significantly for both genders, from 11% to 7% for men and from 25% to 16% for women. Similarly, the coefficient on length of stay also decreases suggesting that we initially overstated its effect in the baseline specification. On the other hand our variable of interest measuring the presence of a CBO increase significantly from 0.02% to 0.4% for men and from 0.4% to 1.5% for women and the effect is now statistically significant for Maghreb women. This suggest that we initially under estimated the effect of a CBO particularly on Maghreb women's labour force participation.

The categorical variable on cohort of arrival reveals that individuals who migrated in the 1950's and 1960's had labour force participation rates similar to natives. Only migrant males between 1964 and 1972 were more likely to participate in the labour force than natives³¹. However, from the 1980's the estimated coefficients are negative and are statistically significant for all genders from the beginning of the 1990's and has been increasing overtime. This is consistent with the historical facts described earlier surrounding the macroeconomic and labour market conditions of France over the past decades. Our coefficient estimates for other variables are robust to controlling for cohort effects.

Employment:

Table [1.9] reports the results from estimating the baseline employment model and table [1.2] presents the marginal effects. The coefficient estimate for immigrant status is negative and statistically significant indicating that young immigrants arriving newly in France have a lower

³¹This is consistent with our earlier documentation of labour recruitment programs.

	(1)	(1)	(2)	(2)
	Males	Males	Females	Females
	Active	Active	Active	Active
Immigrant	-0.114***	-0.259***	-0.0705***	-0.160***
Ũ	(-12.44)	(-24.70)	(-4.38)	(-8.43)
Treated dept	-0.0389***	-0.00287	-0.0388***	-0.00268
	(-5.90)	(-0.37)	(-5.89)	(-0.35)
Post treatment	0.00719^{***}	0.0671^{***}	0.00766***	0.0686***
	(2.97)	(23.08)	(3.15)	(23.53)
Treat*Post	0.00348**	-0.000929	0.00336**	-0.00121
	(2.25)	(-0.49)	(2.18)	(-0.64)
Immigrant*treat*post	0.000284	0.00573	0.00434	0.0153**
	(0.04)	(0.77)	(0.66)	(1.99)
Length of stay	0.00653^{***}	0.00902***	0.00406^{***}	0.00436***
	(8.94)	(10.95)	(3.74)	(3.29)
Length of stay sq	-0.0000745^{***}	-0.0000765***	-0.0000508***	-0.0000359
	(-5.60)	(-5.05)	(-2.77)	(-1.47)
cohort = 1956			0.0158	0.0463^{*}
			(0.77)	(1.65)
cohort = 1964			0.0114	0.0234
			(0.79)	(1.23)
cohort = 1972			0.0294^{**}	-0.0184
			(2.47)	(-1.06)
cohort = 1980			-0.00413	-0.00663
			(-0.34)	(-0.47)
cohort = 1988			-0.0158	-0.0280*
			(-1.26)	(-1.88)
cohort=1996			-0.0256*	-0.00976
			(-1.95)	(-0.64)
cohort=2004			-0.0263*	-0.0908***
			(-1.95)	(-5.33)
cohort=2012			-0.0599***	-0.160***
			(-3.23)	(-7.40)
Observations	1106101	1160667	1106101	1160667

Table 1.1: Average marginal labour force participation rates

t statistics in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

probability of obtaining a job ((about 24% for men and 40% for females)) compared to natives with similar demographic characteristics and skills. The estimated gap is much larger for Maghreb women than men. This follows from our previous discussion on immigrant women's labour force participation. The estimated effect of the presence of a CBO though has a positive sign for all genders but is only statistically significant for Maghreb women. Its estimated effect for Maghreb women is also much larger relative to Maghreb men (about 0.7% for men and 3.7% for females). The estimate on the speed of integration, length of stay is positive and significant. The control variables all have the expected sign. The probability of being employed increase with age and education and is relatively lower for those living in urban areas. Marital status have opposing effects for men and women.

Employment and Cohort effects

In column [2] of table [1.15] we estimate the model including cohort effects and present the marginal effects in column 3 and 4 of table [1.2]. Once we control for cohort effects, the coefficient on immigrant status significantly decreases from 24% to 17% for men and from 40% to 28% for women whilst the coefficient on the role of a CBO becomes larger increasing from 0.7% to 0.8% for men and from 3.7% to 4.3% for women but remains significant only for Maghreb women. This means that young Maghreb immigrants newly arriving in France have relatively better employment prospects than the overall Maghreb immigrant population. More importantly, Maghreb women located in departments where CBO's are present tend to have even higher prospects. Our estimate on the length of stay also decrease slightly. The estimated coefficient only decreases slightly and is identical for both genders. All the other control variables remain robust to controlling for cohort effects.

Wages

We first impute the missing data for hourly wage and then estimate our proposed model. Borjas (2015) finds immigrants year of arrival in the US had a differential effect on earnings and also different growth rates on earning with recent immigrants earning lower and having a lower growth rate of earnings. This paper controls for this by including migrants length of stay as a factor variable measuring the number of years since first arrival in the host country. To satisfy the exclusion restriction proposed by Heckman (1979), we use marital status, number of children in the household and the size of the household as our selection variables.

Table [1.19] presents the results from estimating the effect on earnings using the Heckman model. The results reveal that newly arrived immigrants both males and females on average earn less than natives with comparable demographic characteristics and skills. However, this earning differential is larger for males compared to females. The paper does not find any evidence that the presence of a CBO have any effect on earnings of Maghreb immigrants.

	(1)	(1)	(2)	(2)
			(2)	(2)
	males	males	remales	Females
T • /	Employed	Employed	Employed	Employed
Immigrant	-0.235***	-0.406***	-0.172***	-0.276***
	(-23.90)	(-32.14)	(-9.30)	(-12.60)
Treated dont	0.0670***	0.00005	0 0679***	0.00009
Treated dept	-0.0078	(1.07)	-0.0073	(1, 10)
	(-9.07)	(1.07)	(-9.01)	(1.18)
Post treatment	-0.0310***	0.0457***	-0.0306***	0.0470***
i ost treatment	(1114)	(14.44)	(10.08)	(14.81)
	(-11.14)	(14.44)	(-10.50)	(14.01)
Treat*Post	0.00585***	-0.00192	0.00583***	-0.00203
11000 1 000	(3, 30)	(-0.93)	(3.29)	(-0.98)
	(0.00)	(0.50)	(0.20)	(0.50)
Immigrant*treat*post	0.00738	0.0371^{***}	0.00880	0.0427^{***}
G 1	(1.10)	(4.33)	(1.25)	(4.81)
		()	(-)	(-)
Length of stay	0.00605^{***}	0.00874^{***}	0.00379^{***}	0.00600^{***}
0 1	(7.75)	(9.11)	(3.13)	(3.90)
Length of stay sq	-0.0000177	-0.0000271	0.0000168	-0.0000103
	(-1.22)	(-1.56)	(0.80)	(-0.37)
cohort = 1956			-0.0836***	-0.0394
			(-3.00)	(-1.13)
1 1004			0.0000*	0.0220
cohort=1964			-0.0309*	-0.0320
			(-1.86)	(-1.42)
achort-1072			0.00040	0.0066***
conort=1972			(0.70)	-0.0900
			(-0.70)	(-4.82)
cohort-1980			-0.0356***	-0.0697***
000010-1000			(-2,70)	(-4.25)
			(-2.10)	(4.20)
cohort = 1988			-0.0485***	-0.0995***
			(-3.43)	(-5.81)
			(0.10)	(
cohort = 1996			-0.0500***	-0.0550***
			(-3.41)	(-3.16)
			. /	. ,
cohort=2004			-0.0440^{***}	-0.130***
			(-2.78)	(-7.07)
cohort=2012			-0.0768***	-0.183***
			(-3.63)	(-7.75)
Observations	1106101	1160667	1106101	1160667

Table 1.2: Average marginal employment probabilities

t statistics in parentheses * p<0.1, ** p<0.05, *** p<0.01

Network Effects

Though we include department and time fixed effects in our above analysis, one might argue that the analysis may not uncover the actual impact of the presence of CBO's on labour outcomes due to the following reasons; first, the size of the immigrant population which has been traditionally used as a measure of social network is excluded in the analysis. Hence our estimated coefficients may in addition to other things be capturing this effect. Immigrants location decisions may be influenced by other unobserved characteristics that are correlated with labour outcomes. Immigrants may choose to locate in departments where labour prospects are higher. As highlighted earlier, the presence of networks (measured by the size of the immigrant population from his origin country) lowers the migration cost and hence migrants are more likely to choose to locate in this places so as to maximize their returns from migration.³² Additionally, existing immigrants are known to provide support to new migrants. This is popularly known as the "Enclave effect".³³

As a solution to the above problem, we follow the existing literature and include the stock of the Maghreb population in each department. We instrument the distribution of the current stock of the Maghreb population with its historical distribution in 1968 (a period long enough to be uncorrelated with current outcomes);

$$Imig_{d,t} = \Sigma \frac{imig_{d,1968}}{imig_{1968}} * imig_t$$

The distribution of the population over 30 years ago is strongly correlated with the distribution of the population today, however it is reasonable to assume that the location decision of immigrants over thirty years ago are uncorrelated with current labour market outcomes.

Networks and labour force participation

Table [1.16] presents the result after the inclusion of the network effects. Column [1] presents the results from estimating the model without accounting for the presence of a CBO. The estimated effect of the network is positive and statistically significant with the effect for Maghreb women being much larger. This means that residing in department with higher co-ethnic's increases the probability of participating in the labour force, this effect being more pronounced for women. The coefficient on immigrant status more or less remains the same as the baseline estimate presented in table [1.16] column [2]. Similarly, most of the other variables are fairly unaffected.

In column [2] the results from estimating the full model is presented. Noticeably, the coef-

³²The location decision of migrants have been studied by Jayet et al. (2010a) for migrants in Italy, Jayet and Ukrayinchuk (2007) for immigrants in France, 'Jayet et al. (2016) for immigrants in Belgium and Borjas (1994) for immigrants in the U.S. Attempts have also been made to study the role of networks measured by the migrant stock in facilitating or attracting immigrants.

³³This strategy was first proposed by Abowd and Freeman (1991), Edo and Toubal (2017) also applied similar strategy in studying the effect of immigration on electoral support in France, Edo et al. (2019) showed that this theory actually holds for France.

ficient on the network effect changes slightly for both men and women in opposite ways. But the sign and level of significance remain unaltered. This means that the presence of a CBO amplifies the network effect for women and slightly reduces its effect for men. Though the estimated coefficient for the presence of a CBO is positive, its effect on labour force participation is only significant for women. The effect of time spent in the destination country remains fairly the same as our initial estimates. On the other hand, the estimated coefficients for the cohort effects are much larger but follows a similar pattern as our earlier estimates. The estimated coefficients on the other variables remains fairly the same.

Networks and employment

Table [1.17] presents the result after controlling for network effects. Column [1] estimates the model without including the presence of a CBO while in column [2] this is included. The estimated network effect is negative for Maghreb men and positive for Maghreb women with both coefficients being statistically significant. The coefficient on immigrant status only reduces slightly once the network effect is controlled for and the role of a CBOs omitted. In column [2], once we include the role of a CBOs, the estimated coefficients on the network effect and immigrant status changes only slightly but the pattern remains the same. The coefficient for the other control variables remains quite similar.

Networks and Earnings

The effect of the presence of a CBO has a diluted impact knowing that not all individuals living in the department might directly benefit from it, instead what we actually estimate here is the effect of the intention to treat between treated and control departments. Hence the results reported here could be seen as lower bound estimates of the effect of a CBO, also because of the fact that some departments taken here as treated might have had an a CBO that was dissolve before 2012. Additionally, both treated and control departments might have other organizations other than those established by the Maghreb immigrants themselves providing similar services for all immigrants regardless of origin.

1.6.1 Robustness checks

One of the challenges with using a difference-in-differences strategy is the impossibility to test the parallel trend assumption on which it relies. In this specific case the assumption is that, labour outcomes in treated and control departments would follow a similar trend absent the presence of a CBO. To investigate the parallel trend assumption, we rely on the years preceding the registration of a CBO to test whether estimated changes in employment levels between treated and control departments were significantly different during pre-treatment years. Fortunately for us, sufficient data is available prior to the treatment period (first CBO's were registered six years after our initial starting period).

In table [1.20], we compare pre-treatment average labour force participation rates between treated and control departments. The difference in pre-treatment means in labour force participation rates between departments were CBO's are present and in departments where they are absent is not statistically significant. That is to say average labour force participation rates followed a similar path in both groups prior to the treatment. However, we observe a significant difference in characteristics of individuals located in treated and control departments as well as its composition. Notably is the large fraction of immigrants located in the treated departments prior to the treatment, this however is not very surprising noting that this a CBOs are actually created by the immigrants themselves. Other characteristics such as the gender composition is not significant. We carry out the same analysis for employment rates between the two departments and report the results in [1.21]. Similar to labour force participation, we do find any significant differences between the two groups. Aside from comparing aggregate outcomes between the two groups, we also restricted the data to only immigrants and repeat the same analysis for both labour force participation and employment, the results do not change and the difference is statistically insignificant. In fact, we find the difference in individual characteristics is less stronger. This increases the confidence for our initial estimates. When we instead repeat the same analysis for hourly wages adjusted for inflation, we find that there exists a diverging pre-treatment trend in favor of treated departments.

Inward and outward Migration

Another identification issue that may challenge our results is the possibility that migration between departments is the driving force behind the results we observe. Natives might negatively responds to an increase in the stock of the immigrant population or poor labour outcomes by migrating out of this departments (Borjas (2006)). Alternatively, it could also be that immigrants who are facing difficulty in integrating in the labour market might move out of the department in search of better opportunities. This would create more job opportunities for both immigrants and natives that do not migrate and biasing our estimates upward. Another possibility which is less of an issue is that, if CBOs are indeed successful in improving labour outcomes this might attract more immigrants in the department mostly those with poor labour outcomes biasing our estimated effect downward. Unfortunately we do not have sufficient data to test for this in our analyses. The FLFS ask questions about migration status only for the year preceding the survey.³⁴ However, the possibility that our results are severely affected by this is mitigated if not completely ruled out because the analysis is conducted at an aggregate level, the second largest geographical sub-grouping in France less affected by migration. Edo

 $^{^{34}\}mathrm{About}$ 97.5% of natives and about 98% of immigrants respond that they did not change housing over the last year.

and Toubal (2017) Migration out of a department is less common compared to migration from neighbourhoods or municipalities.

Displacement

Furthermore, one may be tempted to argue that a positive relative higher employment levels in treated departments could be as a result of a displacement effect. An increase in the labour force arising from an increase in the immigrant population increases competition between less skilled natives and immigrants, employers replace the less skilled native workers with immigrants at a lower cost increasing unemployment rates of less skill natives and reducing the labour force participation of this groups. However, previous studies by Fromentin (2013) for France and Abowd and Freeman (1991) for U.S finds no significant evidence that inflows of immigrant leads to large and or systematic effects on employment or unemployment rates of less skilled natives. Fromentin (2013) studying the relationship between immigration and unemployment in France found no aggregate increase in unemployment in the long run due to immigration and instead finds that immigration have a negative effect on unemployment and a positively weak effect on employment in the long-run. We therefore rely on this results to argue that this is not the mechanism at play for our analysis.

Taking all the pieces of results together, one can infer that the main mechanism through which a CBO may affect labour outcome is by empowering individuals with relevant skills necessary to penetrate the labour market, thus increasing their marketability in the labour market. The result also suggests that this CBO's helps to improve the quality and density of the network through the interaction of skill enhancement and information dissemination.

The provision of information about job opportunities particularly to newly arrived immigrants and to individuals with low skills who in addition to having little education are also unlikely to be aware of the processes involved in applying for a job such as enrolling with an employment agency or preparing a CV gain disproportionately more from the services offered by this institutions. Our findings do rule out the possibility that effect we observe is mainly driven by a network effect, that is to say the immigrants stock alone or living in an enclave is what drives our result. However, the fact that we do find a stronger effect of CBO's once interacted with the stock of the immigrant population suggest that the information role of a CBO's is amplified by the size of the network.

1.6.2 Propensity Score Matching (PSM)

This study proposes to to use a method akin to a diff-in-diff, however, the main challenge is to address concerns linked to the endogeneity of CBO's. The usual way to deal with such endogeneity is to adopt an Instrumental variable approach³⁵. The existing literature provides little

³⁵A valid instrument in this case has to be i) able to explain the probability of having a CBO in a department and ii) exogenous to labour outcomes. Finding such an IV is a challenging task.

guidance on potential instruments that can be used to address the endogenity of networks³⁶. Possible IV's for this study include factors related to the economic conditions in the origin countries that may encourage people to migrate and thus creating a need for integration support in the host country, but these factors should be uncorrelated with labour market conditions in the host country. However, though this may explain the formation of social networks. It does not help in explaining why networks emerge in certain departments instead of others. Therefore, what is needed in addition to explaining outward migration from origin countries is something that can also help explain the emergence of this networks in different departments at different periods and that is uncorrelated with current labour market outcomes in the destination country.

However, this is a daunting task. The main problem of finding an IV for CBO's is that information related to CBO's and economic conditions in a department overlap. Information related to CBO's in a department are likely to be correlated with the outcome variables, making such variables invalid instruments. Number of highly trained doctors, networks of war veterans, sport clubs, employment in manufacturing farms 5 or 10 years ago are all possible valid alternative IV's. But this information is not readily available at department level for long periods or are mostly measured with error. Therefore due to data limitation identification of a suitable instrument is not possible for this study.

This study instead relies on the suggestion and evidence provided by McKenzie et al. (2010) and McKenzie and Sasin (2007) that in the absence of a good IV, within non-experimental methods, a PSM performs comparatively better as using a poor IV leads to an increase in the bias. This study therefore employs a PSM approach and used various other matching methods as robustness checks.

The basic idea of the PSM is to estimate the ATE (in this study I estimate the Intention to Treat ITT) related to the presence of a network on the labour market outcome of interest³⁷. This study estimates the ITT because information on direct beneficiaries is not available. However, large spillover effects are expected from the group of those who actually benefit from the networks. Comparison of average difference in labour outcomes between treated and non-treated departments is made while matching the two groups of individuals with similar characteristics and then any observed difference is attributed to the treatment.

Separating the analyses by gender and restricting the sample to only Immigrants, I estimate the average treatment effects for two of the three labour outcomes analysed earlier, labour force participation rates and employment rates. The results for Male on labour force participation are consistent with the previous findings, i.e presence of a CBO has no effect on labour force participation for male immigrants. For other variables, my findings seems to suggest once we

 $^{^{36}}$ For instance, Munshi (2003) adopted an instrumental variable approach and used rainfall in the origincommunity as an instrument for the size of the network at the destination country.

 $^{^{37}}$ See Abadie and Imbens (2016)

restrict our sample and perform a propensity score matching, we only find suggestive evidence, but the effect is not statistically significant.

1.7 Further analyses

In this section, we further explore the effect of this CBO's on the labour market integration of immigrants by conducting various heterogeneity analyses.

Heterogeneity by country of origin

We first dis-aggregate our immigrant indicator into three different indicators each representing immigrants from a particular country of origin. Our results presented in table [1.22] and average marginal effects presented in table [1.3] shows that on average, among the Maghreb immigrants, those from Algeria and Tunisia are less likely to participate in the labour force (about 8% and 7.5% for males and 16% and 17.5% for females respectively) relative to comparable natives. In terms of employment prospects, a similar pattern is observed. Algerian and Tunisian men are about 18% less likely to be employed while for females i is about 27%.

Focusing on the effect of CBO's, consistent with our earlier findings, we do not find any effect of CBO's on labour force participation rates for males. For females, we find that the observed effect is largely driven by the effect on Algerians, about 3.2%. With regards to employment, again we find a significant effect only for women despite the positive coefficient on males. Moroccan immigrants seems to benefit less from these institutions.

Heterogeneity by length of stay

We generate a dummy for immigrant that arrive recently, those with a length of stay of 5 years or less and interact this dummy with the treatment dummy. Our results suggest that for both genders, recently arrived immigrants disproportionately benefit from residing in a department where an association is present both in terms of labour force participation and employment. However, this effect is statistically significant only for immigrants with a longer length of stay. Table [1.23] presents the full results and table [1.4] presents the marginal effects.

Heterogeneity by age group

A major concern for both scholars and policy makers and among natives and immigrants is the integration of the young in the labour market. As such we asses the impact of these associations on labour force participation and access to employment for immigrants below the age of 25. We generate a variable for this category of the immigrant population and interact it with the treatment dummy. Our estimates show that on average, young men and women in France below the age of 25 are about 12.5% and 14.7% respectively less likely to participate in the labour

	(1)	(2)	(3)	(4)
	Active	Active	Employed	Employed
	Male	Female	Male	Female
Algeria	-0.0794^{***}	-0.164^{***}	-0.184***	-0.275***
	(-4.56)	(-8.10)	(-9.29)	(-11.75)
Tunicia	-0 0755***	-0 176***	-0 180***	-0 283***
Tumsia	(2.42)	(7.06)	(7.60)	(0.73)
	(-3.43)	(-7.00)	(-7.09)	(-9.73)
Morocco	-0.0607***	-0.151***	-0.157***	-0.273***
	(-3.57)	(-7.49)	(-8.06)	(-11.73)
Treated dept	-0.0387***	-0.00267	-0.0670***	0.00990
	(-5.87)	(-0.35)	(-8.98)	(1.17)
Post treatment	0.00770***	0 0686***	-0.0306***	0 0470***
i ost treatment	(3.17)	(23.53)	(-10.96)	(14.81)
	(0.17)	(20.00)	(-10.50)	(14.01)
Treat*Post	0.00334^{**}	-0.00121	0.00578^{***}	-0.00203
	(2.16)	(-0.64)	(3.26)	(-0.98)
	~ /			
Algerian*treat*post	0.0121	0.0324^{***}	0.0134	0.0500^{***}
	(1.33)	(2.96)	(1.35)	(3.94)
Tunisian*treat*nost	0.00558	0.0215	0.0153	0.0/38*
rumstan treat post	(0.20)	(1.04)	(0.81)	(1.81)
	(0.29)	(1.04)	(0.01)	(1.01)
Moroccan*treat*post	-0.00392	-0.00623	0.00405	0.0336**
-	(-0.39)	(-0.54)	(0.38)	(2.50)
Observations	1106101	1160667	1106101	1160667

Table 1.3: Average marginal effect by country of origin

 $t\ {\rm statistics}\ {\rm in}\ {\rm parentheses}$

* p < 0.1, ** p < 0.05, *** p < 0.01

	(1)	(2)	(3)	(4)
	Active	Active	Employed	Employed
	Male	Female	Male	Female
Imig less than 5yrs stay	-0.0580***	-0.175***	-0.179***	-0.284***
	(-3.20)	(-7.85)	(-8.48)	(-10.36)
Imig greater than 5yrs stay	-0.0498**	-0.0899***	-0.151***	-0.215***
	(-2.41)	(-3.91)	(-6.64)	(-8.10)
Treated dept	-0.0388***	-0.00258	-0.0673***	0.0100
-	(-5.89)	(-0.34)	(-9.01)	(1.19)
Post treatment	0.00760***	0.0684***	-0.0307***	0.0468***
	(3.13)	(23.46)	(-11.00)	(14.75)
Treat*Post	0.00337**	-0.00123	0.00583***	-0.00204
	(2.18)	(-0.65)	(3.29)	(-0.98)
Imig less than 5yrs stay*treat*post	-0.0165	0.0219	0.0160	0.0334
	(-1.03)	(1.10)	(0.88)	(1.28)
Imig greater than 5yrs stay*treat*post	0.00713	0.0154^{*}	0.00784	0.0442***
	(1.00)	(1.88)	(1.05)	(4.75)
Observations	1106101	1160667	1106101	1160667

Table 1.4: Average marginal effect by length of stay

t statistics in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

force and to be employed relative to people above the age of 25. Young Maghreb immigrants are even more less likely to participate in the labour force or to be employed, about 4% and 12% respectively. Interestingly enough, our data reveal that immigrants above the age of 25 are even more less likely to participate in the labour force or be employed compared to younger immigrants. Our variable of interest shows a heterogeneous effect of CBO's on labour market integration of immigrants distinguished by age group. Whilst Maghreb men's labour force participation rates are unaffected, the employment prospects of young Maghreb men are higher in departments where a CBO is present by about 4%. On the contrary, for Maghreb women, we find opposing effect for young and older Maghreb immigrant. Labour force participation rates for Maghreb women is about 6% lower while that of older Maghreb women increases by about 2.3% and both effects are statistically significant. With regards to employment prospects, the effect is only significant for older women.

1.8 Conclusion

This paper investigates the role of Maghreb immigrant local economic associations also known as Community Based Organisations (CBO's) on the economic integration of Maghreb immigrants in France. Previous studies has mainly relied on familial ties and the presence of co-ethnics

	(1)	(2)	(3)	(4)
	Active	Active	Employed	Employed
	Male	Female	Male	Female
Native youth less than 25 yrs	-0.125***	-0.147***	-0.121***	-0.138***
	(-58.64)	(-54.10)	(-51.74)	(-48.17)
Young immigrant less 25	-0.0384^{**}	0.0372	-0.113***	-0.125^{***}
	(-2.19)	(1.59)	(-4.99)	(-4.18)
		0.01.0***	0 10 1***	0 000***
Elderly immigrant older 25	-0.0940***	-0.218***	-0.194***	-0.309***
	(-5.83)	(-11.50)	(-10.68)	(-14.09)
Treated dent	-0.0385***	-0.00300	-0.0673***	0.00916
ileated dept	-0.0585	(-0.39)	(-9.02)	(1.00)
	(-5.60)	(-0.00)	(-3.02)	(1.05)
Post treatment	0.00755^{***}	0.0681***	-0.0314***	0.0458^{***}
	(3.11)	(23.41)	(-11.26)	(14.47)
	()	()	()	()
Treat*Post	0.00303^{**}	-0.00117	0.00559^{***}	-0.00197
	(1.96)	(-0.62)	(3.16)	(-0.95)
Young immigrant*treat*post	0.00618	-0.0595***	0.0397^{*}	0.0146
	(0.40)	(-2.65)	(1.89)	(0.50)
	0.00520	0.0000***	0.00770	0.0440***
Elderly immigrant [*] treat [*] post	0.00532	0.0230^{+++}	0.00776	0.0448^{+++}
	(0.78)	(2.94)	(1.09)	(4.95)
Observations	1106101	1160667	1106101	1160667

Table 1.5: Average marginal effect by age group

 $t\ {\rm statistics}\ {\rm in}\ {\rm parentheses}$

* p < 0.1, ** p < 0.05, *** p < 0.01

as the main measure of immigrants social networks. However, as we may expect the ability of such measures of networks is quite limited partly due to a lack of well defined structure. Community Based Organisations on the other hand, tend be a bit more formalised with well defined objective and structures and at times tend to be supported by or have partnerships with local governments and other stakeholders. They tend to have more information about means of obtaining job, existing job opportunities and information about how to access social welfare³⁸. Therefore one of the main contribution of this study is by extending the literature to the analysis of the role of formalised social structures on labour outcomes of immigrants. This is essential to understand how government policies could affect social networks. This study attempts to fill this gap by focusing on a relatively large subgroup of immigrants with a long migration history to France to draw useful insights on their integration levels. We find that on average the presence of an association is associated with a significant increase in labour force participation and the probability of being employed for young and newly arrived Maghreb women. The estimated effects for Maghreb men though positive is not statistically significant. Furthermore, this study do not find any evidence that the increase in labour outcomes for females is towards low quality jobs measured by earnings. We find that newly arrive migrants living in departments where such associations exist enjoy a faster rate of integration relative to those in non treated departments. However, this study cannot measure the net effect on beneficiaries due to lack of adequate data. Therefore, we do not claim that all the observe effect is due to this institutions, but we strongly believe that this institutions partly contributed to this observed outcomes. For the subgroup of direct beneficiaries, the estimated effect is likely to be much larger.

Potential policy implication

The findings of the research has several policy implication. First, it identifies the most disadvantage subgroup of migrants for whom a larger opportunity for improvement exist. This highlights that government integration policies should prioritise such groups to maximise the gains from such interventions. Second, due to the proximity of associations to migrants and their voluntary and altruistic nature, they could be potential partners for governments and other international organisations concerned about helping immigrants integrate in the labour market and maximise the potential benefits of migrants. Therefore government could tab from expertise of such groups by involving them in the policy formulations concerning the integration of immigrants. Thirdly, government should enact policies that ensure a fair treatment of individuals irrespective of origin. More importantly, government could improve labour market returns by recognising relevant foreign qualifications. Finally information about employment opportunities is not enough, instead this have to be accompanied by some forms of assistance

 $^{^{38}}$ Unfortunately, we are unable to investigate if this institutions makes immigrants more reliant on social welfare benefits.

ranging from providing language training classes and helping to access these services.

1.9 Appendix



Figure 1.1: Maghreb population in France 1960 - 2015 as a share of the Foreign population

Figure 1.2: Average employment rate in France 1960 - 2015 conditional on being active



	Female		Male	
	Native	Maghreb	Native	Maghreb
1990				
Basic Educ	52.89	69.11	45.36	65.32
High Sch Edu	22.51	13.47	31.52	14.51
Post high sch	19.38	12.85	15.22	12
Post-grad degree	5.220	4.570	7.900	8.170
Total	100	100	100	100
2012				
Basic Educ	25.48	53.02	25.07	45.60
High Sch Edu	22.06	12.65	29.67	18.63
Post high sch	35.68	21.79	29.40	20.07
Post-grad degree	16.78	12.54	15.86	15.70
Total	100	100	100	100

Table 1.6: Percentage of population based on Education qualifications 1990 $\ 2012$

Table 1.7: Education attainment rates

	Female		Male	
	Native	Maghreb	Native	Maghreb
Basic Educ	31.15	54.78	30.18	48.05
High Sch Edu	20.43	13.46	17.61	13.42
Post high sch	34.84	20.21	39.37	23.73
Post-grad degree	13.57	11.56	12.84	14.80
Total	100	100	100	100

Table 1.8: Labor Force Participation rates 1990 $\ 2012$

	Female		Male	
	Native	Maghreb	Native	Maghreb
1990				
employed	58.95	34	80.15	71.29
unemployed	7.730	9.910	5.580	12.83
inactive	33.32	56.09	14.26	15.89
Total	100	100	100	100
2012				
employed	67.98	41.51	75.25	62.14
unemployed	7.870	11.53	8.430	16.76
inactive	24.15	46.97	16.33	21.10
Total	100	100	100	100

Table 1.9: Labor force participation rates

	Female		Male	
Labor Market Status	Native	Immigrant	Native	Immigrant
employed	60.42	42.78	69.37	61.71
unemployed	7.970	11.78	7.520	14.27
inactive	31.60	45.43	23.11	24.02
Total	100	100	100	100

Female Male occupation Native Immigrant Native Immigrant unskilled-manual workers 11.6315.2022.66 30.19 skilled-manual workers 3.6303.10022.4323.41Administrative employees 65.5763.9319.5917.36Skilled workers 19.17 17.7835.3229.04Total 100100 100 100

Table 1.10: Occupational Distribution

Variable	Mean	Std.Err.	90% Conf. Interval	
age	42.13	0.0290	42.08	42.19
sexe	0.496	0.000398	0.495	0.496
imig	0.0522	0.000545	0.0511	0.0533
\exp	21.10	0.0294	21.04	21.16
cohab	0.720	0.00103	0.718	0.722
married	0.562	0.00138	0.560	0.565
no child 3	0.0969	0.000584	0.0958	0.0981
no child 18	0.353	0.00327	0.346	0.359
no in house	2.926	0.00411	2.918	2.934
Basic educ	0.349	0.00123	0.346	0.351
High sch	0.275	0.000812	0.274	0.277

0.000916

0.000876

0.00339

0.00342

0.00135

0.258

0.115

0.247

0.599

0.138

0.261

0.119

0.260

0.612

0.143

Post highsch

Post grad

Rural

Urban

Paris

0.259

0.117

0.253

0.606

0.141

Table 1.11: Sample Means



Figure 1.3: Graph of French Departments

This figures plots Departments with at least one registered association in 2000 and 2012.

	Female		Male	
	Native	Maghreb	Native	Maghreb
Control				
employed	60.82	39.77	70.36	61.47
unemployed	7.770	11.52	6.970	13.45
inactive	31.41	48.71	22.67	25.08
Total	100	100	100	100
Treatment				
employed	60.22	43.59	68.87	61.77
unemployed	8.080	11.85	7.800	14.49
inactive	31.70	44.56	23.34	23.73
Total	100	100	100	100

Table 1.12: Labor Force Participation rates in treated and control groups

	Female		Male	
	Native	Maghreb	Native	Maghreb
Control				
Basic Educ	33.19	58.31	31.20	50.94
High Sch Edu	20.11	12.65	16.95	11.93
Post high sch	36.50	20.49	42.56	24.36
Post-grad degree	10.20	8.550	9.290	12.78
Total	100	100	100	100
Treatment				
Basic Educ	30.14	53.83	29.66	47.26
High Sch Edu	20.59	13.67	17.95	13.83
Post high sch	34.02	20.14	37.74	23.56
Post-grad degree	15.25	12.36	14.66	15.35
Total	100	100	100	100

Table 1.13: Education attainment rates in treated and control departments

	(1)	(1)	(2)	(2)
	Males	Males	Females	Females
	Active	Active	Active	Active
Immigrant	-0.618***	-0.973 ^{***}	-0.381***	-0.599***
	(-12.44)	(-24.64)	(-4.38)	(-8.42)
Treated dept	-0.210***	-0.0108	-0.210***	-0.0100
	(-5.90)	(-0.37)	(-5.89)	(-0.35)
Post treatment	0.0389^{***}	0.252^{***}	0.0415^{***}	0.257^{***}
	(2.97)	(23.03)	(3.15)	(23.48)
Treat*Post	0.0188^{**}	-0.00348	0.0182^{**}	-0.00453
	(2.25)	(-0.49)	(2.18)	(-0.64)
${\rm Immigrant}^*{\rm treat}^*{\rm post}$	$\binom{0.00153}{(0.04)}$	$ \begin{array}{c} 0.0215 \\ (0.77) \end{array} $	0.0235 (0.66)	0.0574^{**} (1.99)
Age=28	1.405^{***}	1.227^{***}	1.405^{***}	1.227^{***}
	(176.83)	(161.50)	(176.85)	(161.54)
Age=34	1.996^{***}	1.637^{***}	1.995^{***}	1.638^{***}
	(180.31)	(189.91)	(180.31)	(189.99)
Age=40	1.980^{***}	1.823^{***}	1.980^{***}	1.823^{***}
	(167.95)	(199.25)	(167.93)	(199.24)
Age=46	1.849^{***}	1.768^{***}	1.849^{***}	1.768^{***}
	(161.24)	(196.10)	(161.27)	(196.00)
Age=52	1.612^{***}	1.464^{***}	1.612^{***}	1.464^{***}
	(145.74)	(165.93)	(145.69)	(165.82)
Age=58	0.862^{***}	0.884^{***}	0.861^{***}	0.883^{***}
	(83.34)	(97.77)	(83.23)	(97.68)
Age=64	-0.657***	-0.347 ^{***}	-0.658 ^{***}	-0.348 ^{***}
	(-58.01)	(-35.99)	(-58.12)	(-36.12)
Length of stay	0.0353^{***}	0.0338^{***}	0.0220^{***}	0.0164^{***}
	(8.94)	(10.95)	(3.73)	(3.29)
Length of stay sq	-0.000403 ^{***}	-0.000287***	-0.000275 ^{***}	-0.000134
	(-5.60)	(-5.05)	(-2.77)	(-1.47)
Married	0.387^{***}	-0.0822***	0.387^{***}	-0.0817***
	(53.35)	(-15.49)	(53.35)	(-15.39)
High sch	0.198^{***}	0.331^{***}	0.198^{***}	0.330^{***}
	(27.88)	(55.57)	(27.96)	(55.51)
1st level tertiary	0.448^{***}	0.453^{***}	0.448^{***}	0.453^{***}
	(74.07)	(85.74)	(74.11)	(85.64)
Postgraduate	0.488^{***}	0.504^{***}	0.489^{***}	0.504^{***}
	(47.42)	(60.79)	(47.48)	(60.73)
Urban	-0.101***	-0.0774***	-0.101***	-0.0769***
	(-16.00)	(-14.48)	(-15.99)	(-14.38)
size of the household	$\binom{0.000845}{(0.32)}$	-0.0843*** (-34.64)	0.000613 (0.23)	-0.0844 ^{***} (-34.68)
children below 18 years	-0.0122***	-0.186***	-0.0119***	-0.186***
	(-3.23)	(-55.94)	(-3.15)	(-56.01)
cohort=1956			$ \begin{array}{c} 0.0874 \\ (0.75) \end{array} $	$ \begin{array}{c} 0.180 \\ (1.59) \end{array} $
cohort=1964			$ \begin{array}{c} 0.0625 \\ (0.78) \end{array} $	$ \begin{array}{c} 0.0891 \\ (1.21) \end{array} $
cohort=1972			0.165^{**} (2.38)	-0.0680 (-1.07)
cohort=1980			-0.0223 (-0.34)	-0.0248 (-0.47)
cohort=1988			-0.0838 (-1.28)	-0.103* (-1.91)
cohort=1996			-0.134** (-2.01)	-0.0364 (-0.65)
cohort=2004			-0.138 ^{**} (-2.00)	-0.324^{***} (-5.56)
cohort=2012			-0.304*** (-3.44)	-0.555^{***} (-7.78)
Constant	-0.324***	-0.381***	-0.323***	-0.380***
	(-9.97)	(-14.47)	(-9.93)	(-14.43)
*.dept	Yes	Yes	Yes	Yes
*.annee	Yes	Yes	Yes	Yes
Observations	1106101	1160667	1106101	1160667
r2	0.388	0.264	0.388	0.264

Table 1.14: Labor force participation and cohort effects

 $\begin{array}{c} \begin{array}{c} 1106101\\ \hline r2 \\ \hline 0.388 \\ \hline t \text{ statistics in parentheses} \\ * p < 0.1, ** p < 0.05, *** p < 0.01 \end{array}$

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	(1)	(1)	(2)	(2)
	Males	Males	Females	Females
	Employed	Employed	Employed	Employed
Immigrant	-1.000***	-1.344***	-0.732***	-0.911***
	(-23.87)	(-32.03)	(-9.29)	(-12.59)
Treated dept	-0.288*** (-9.07)	$0.0299 \\ (1.07)$	-0.286*** (-9.01)	$ \begin{array}{c} 0.0328 \\ (1.18) \end{array} $
Post treatment	-0.132***	0.151^{***}	-0.130***	0.156^{***}
	(-11.14)	(14.43)	(-10.98)	(14.80)
Treat*Post	0.0249^{***}	-0.00635	0.0248***	-0.00671
	(3.30)	(-0.93)	(3.29)	(-0.98)
Immigrant*treat*post	$0.0314 \\ (1.10)$	0.123^{***} (4.33)	0.0374 (1.25)	0.141^{***} (4.81)
Age=28	1.207^{***}	1.234^{***}	1.207^{***}	1.235^{***}
	(166.41)	(164.93)	(166.44)	(165.05)
Age=34	1.639^{***}	1.499^{***}	1.639^{***}	1.500^{***}
	(194.11)	(185.97)	(194.15)	(186.06)
Age=40	1.689^{***}	1.635^{***}	1.689^{***}	1.635^{***}
	(186.16)	(196.95)	(186.15)	(196.97)
Age=46	1.650^{***}	1.755^{***}	1.651^{***}	1.755^{***}
	(176.16)	(205.35)	(176.13)	(205.35)
Age=52	1.536^{***}	1.716^{***}	1.536^{***}	1.716^{***}
	(160.79)	(199.98)	(160.74)	(199.92)
Age=58	0.929^{***}	1.326^{***}	0.928^{***}	1.326^{***}
	(101.63)	(153.88)	(101.53)	(153.84)
Age=64	-0.485***	0.220^{***}	-0.486***	0.220^{***}
	(-49.30)	(24.45)	(-49.40)	(24.37)
Length of stay	0.0257^{***}	0.0289^{***}	0.0161^{***}	0.0198^{***}
	(7.75)	(9.11)	(3.13)	(3.90)
Length of stay sq	-0.0000752 (-1.22)	-0.0000896 (-1.56)	$\begin{array}{c} 0.0000716 \\ (0.80) \end{array}$	-0.0000342 (-0.37)
Married	0.476^{***} (80.27)	-0.0993*** (-20.75)	0.476^{***} (80.24)	-0.0993*** (-20.75)
High sch	0.319^{***}	0.453^{***}	0.319^{***}	0.452^{***}
	(48.70)	(77.54)	(48.70)	(77.40)
1st level tertiary	0.449^{***}	0.486^{***}	0.449^{***}	0.485^{***}
	(84.12)	(96.58)	(84.07)	(96.41)
Postgraduate	0.576^{***}	0.645^{***}	0.576^{***}	0.645^{***}
	(64.32)	(81.87)	(64.29)	(81.73)
Urban	-0.153***	-0.0735***	-0.153***	-0.0730^{***}
	(-27.19)	(-14.27)	(-27.15)	(-14.16)
cohort=1956			-0.334*** (-3.18)	-0.129 (-1.14)
cohort=1964			-0.128* (-1.91)	-0.104 (-1.44)
cohort=1972			-0.0401 (-0.70)	-0.311*** (-4.90)
cohort=1980			-0.147*** (-2.77)	-0.226*** (-4.32)
cohort=1988			-0.199 ^{***} (-3.55)	-0.320 ^{***} (-5.92)
cohort=1996			-0.205*** (-3.54)	-0.178*** (-3.20)
cohort=2004			-0.181 ^{***} (-2.87)	-0.417 ^{***} (-7.18)
cohort=2012			-0.308*** (-3.82)	-0.583*** (-7.75)
Constant	-0.459***	-1.112***	-0.459***	-1.112***
	(-16.43)	(-45.07)	(-16.44)	(-45.06)
$^{*.\mathrm{dept}}$	Yes	Yes	Yes	Yes
*.annee	Yes	Yes	Yes	Yes
Observations	1106101	1160667	1106101	1160667

Table 1.15: Employment and cohort effects

 $\frac{12p}{t \text{ statistics in parentheses}} * p < 0.1, ** p < 0.05, *** p < 0.01$

	(1)	(2)	(3)	(4)
	Males	Males	Females	Females
	Active	Active	Active	Active
Active	0.150***	0.670***	0.123*** (3.36)	0.728***
Stock of Maghreb immigrants	(4.83)	(28.26)		(26.43)
Immigrant	-0.382***	-0.588***	-0.394^{***}	-0.644***
	(-5.00)	(-10.07)	(-5.14)	(-11.10)
Length of stay	0.0220***	0.0149^{***}	0.0215^{***}	0.0120^{***}
	(4.34)	(3.78)	(4.23)	(3.05)
Length of stay sq	-0.000259***	-0.0000551	-0.000265***	-0.0000440
	(-3.08)	(-0.77)	(-3.14)	(-0.62)
Age=28	1.401^{***}	1.167^{***}	1.403^{***}	1.156^{***}
	(204.22)	(157.43)	(204.33)	(142.93)
Age=34	1.990^{***}	1.562^{***}	1.992^{***}	1.548^{***}
	(211.65)	(180.25)	(212.22)	(160.21)
Age=40	1.976^{***}	1.742^{***}	1.977^{***}	1.726^{***}
	(203.56)	(188.05)	(203.78)	(165.97)
Age=46	1.845^{***}	1.687^{***}	1.846^{***}	1.672^{***}
	(200.32)	(185.37)	(200.62)	(163.63)
Age=52	1.609^{***}	1.397^{***}	1.610^{***}	1.384^{***}
	(182.09)	(165.02)	(182.58)	(148.66)
Age=58	0.859^{***}	0.841^{***}	0.860^{***}	0.833^{***}
	(103.74)	(109.59)	(103.89)	(103.90)
Age=64	-0.657***	-0.332***	-0.657***	-0.329***
	(-73.44)	(-44.80)	(-73.46)	(-44.32)
cohort=1956	$0.0567 \\ (0.63)$	$0.0241 \\ (0.29)$	$ \begin{array}{c} 0.0812 \\ (0.89) \end{array} $	$ \begin{array}{c} 0.0821 \\ (0.97) \end{array} $
cohort=1964	$ \begin{array}{c} 0.0442 \\ (0.69) \end{array} $	-0.00203 (-0.04)	$\begin{array}{c} 0.0607 \\ (0.94) \end{array}$	$\begin{array}{c} 0.0442 \\ (0.78) \end{array}$
cohort=1972	0.151^{***}	-0.123***	0.162^{***}	-0.0877*
	(2.76)	(-2.58)	(2.93)	(-1.83)
cohort=1980	-0.0304	-0.0643	-0.0238	-0.0373
	(-0.60)	(-1.59)	(-0.47)	(-0.93)
cohort=1988	-0.0855	-0.114***	-0.0854	-0.106**
	(-1.60)	(-2.74)	(-1.60)	(-2.57)
cohort=1996	-0.133**	-0.0379	-0.137**	-0.0499
	(-2.38)	(-0.86)	(-2.45)	(-1.14)
cohort=2004	-0.128 ^{**}	-0.285***	-0.140 ^{**}	-0.320***
	(-2.25)	(-6.18)	(-2.43)	(-6.90)
cohort=2012	-0.291***	-0.509***	-0.305***	-0.552***
	(-3.65)	(-8.92)	(-3.79)	(-9.63)
High sch	0.199^{***}	0.318^{***}	0.199^{***}	0.315^{***}
	(35.25)	(68.39)	(35.26)	(66.83)
1st level tertiary	0.447^{***}	0.433^{***}	0.448^{***}	0.429^{***}
	(94.81)	(101.91)	(94.91)	(97.35)
Postgraduate	0.488^{***}	0.483^{***}	0.488^{***}	0.479^{***}
	(59.38)	(73.71)	(59.45)	(72.01)
Married	0.387^{***}	-0.0745***	0.387^{***}	-0.0736***
	(68.75)	(-18.67)	(68.73)	(-18.49)
children below 18 years	-0.0118 ^{***}	-0.179***	-0.0118 ^{***}	-0.177***
	(-3.93)	(-69.60)	(-3.92)	(-68.20)
size of the household	$\begin{array}{c} 0.0000542 \\ (0.03) \end{array}$	-0.0823*** (-44.13)	$0.000146 \\ (0.07)$	-0.0816*** (-43.73)
Urban	-0.100***	-0.0715***	-0.100***	-0.0700***
	(-20.76)	(-18.18)	(-20.76)	(-17.80)
Treat*Post			0.0135^{*} (1.82)	-0.0322*** (-5.38)
Immigrant*Post-treat			$ \begin{array}{c} 0.0368 \\ (1.25) \end{array} $	0.146^{***} (6.42)
Constant *.dept	-1.651*** (-5.90) Yes	-6.248*** (-29.35) Yes	-1.406*** (-4.27) Yes	-6.775*** (-27.40) Yes
-				
*.annee	Yes	Yes	Yes	Yes
Observations	1105797	1160343	1105797	1160343

Table 1.16: Labor force participation and network effects

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	(1)	(2)	(3)	(4)
	Males	Males	Females	Females
Employed	Employed	Employed	Employed	Employed
Stock of Maghreb immigrants	-0.301***	0.409^{***}	-0.377***	0.455^{***}
	(-10.85)	(16.84)	(-11.67)	(15.99)
Immigrant	-0.693 ^{***}	-0.858 ^{***}	-0.682 ^{***}	-0.940 ^{***}
	(-10.26)	(-14.46)	(-10.13)	(-15.79)
Length of stay	0.0172^{***}	0.0205^{***}	0.0173^{***}	0.0172^{***}
	(3.95)	(5.02)	(3.96)	(4.18)
Length of stay sq	$0.0000469 \\ (0.63)$	$0.0000135 \\ (0.18)$	$\begin{array}{c} 0.0000395 \ (0.53) \end{array}$	0.0000200 (0.27)
Age=28	1.197^{***}	1.212^{***}	1.191^{***}	1.207^{***}
	(186.93)	(181.01)	(176.07)	(171.79)
Age=34	1.625^{***}	1.474^{***}	1.616^{***}	1.467^{***}
	(218.58)	(205.46)	(201.72)	(192.85)
Age=40	1.672^{***}	1.608^{***}	1.663^{***}	1.601^{***}
	(212.58)	(217.41)	(196.52)	(202.69)
Age=46	1.634^{***}	1.725^{***}	1.625^{***}	1.718^{***}
	(207.81)	(224.35)	(193.24)	(207.64)
Age=52	1.519^{***}	1.687^{***}	1.510^{***}	1.680^{***}
	(193.04)	(220.13)	(180.53)	(204.28)
Age=58	0.918^{***}	1.304^{***}	0.913^{***}	1.298^{***}
	(126.18)	(177.96)	(122.35)	(169.12)
Age=64	-0.485 ^{***}	0.219^{***}	-0.483 ^{***}	0.218^{***}
	(-62.66)	(31.14)	(-62.23)	(31.06)
cohort=1956	-0.320***	-0.263***	-0.310***	-0.182**
	(-3.91)	(-3.11)	(-3.76)	(-2.14)
cohort=1964	-0.126**	-0.190***	-0.121**	-0.128**
	(-2.32)	(-3.43)	(-2.21)	(-2.29)
cohort=1972	-0.0347	-0.366***	-0.0306	-0.319***
	(-0.76)	(-7.64)	(-0.67)	(-6.64)
cohort=1980	-0.143***	-0.265***	-0.140***	-0.230***
	(-3.37)	(-6.64)	(-3.30)	(-5.75)
cohort=1988	-0.192***	-0.328 ^{***}	-0.191***	-0.319***
	(-4.29)	(-7.87)	(-4.26)	(-7.70)
cohort=1996	-0.195***	-0.168***	-0.193***	-0.185***
	(-4.20)	(-3.90)	(-4.16)	(-4.30)
cohort=2004	-0.172***	-0.371***	-0.172***	-0.417***
	(-3.38)	(-8.03)	(-3.35)	(-8.97)
cohort=2012	-0.299***	-0.527***	-0.299***	-0.586 ^{***}
	(-4.22)	(-8.71)	(-4.18)	(-9.60)
Married	0.472^{***}	-0.0968***	0.470^{***}	-0.0962***
	(100.26)	(-26.70)	(97.93)	(-26.56)
High sch	0.314^{***}	0.446^{***}	0.312^{***}	0.444^{***}
	(60.81)	(97.92)	(60.24)	(96.19)
1st level tertiary	0.444^{***}	0.478^{***}	0.441^{***}	0.476^{***}
	(106.52)	(121.50)	(104.40)	(118.24)
Postgraduate	0.569^{***}	0.635^{***}	0.566^{***}	0.633^{***}
	(81.51)	(101.64)	(80.57)	(99.93)
Urban	-0.153***	-0.0705***	-0.153***	-0.0693***
	(-35.47)	(-18.43)	(-35.46)	(-18.11)
Treat*Post			0.0387^{***} (5.84)	-0.0241 ^{***} (-4.10)
Immigrant*Post-treat			-0.00440 (-0.18)	0.196^{***} (8.42)
Constant	2.173***	-4.688***	2.861***	-5.100***
*.dept	(8.68)	(-21.64)	(9.81)	(-20.11)
	Yes	Yes	Yes	Yes
*.annee	Yes	Yes	Yes	Yes
Observations	1105797	1160343	1105797	1160343

Table 1.17: Employment and network effects

t statistics in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

	(1)	(2)	(9)	(4)
	(1)	(2)	(3)	(4)
	Males	Males	Females	Females
	wage	wage	wage	wage
Immigrant	-1.165	-1.157	-0.834	-0.824
	(-1.37)	(-1.36)	(-0.54)	(-0.54)
Treat*Post	-0.210*	-0.207*	-0.720***	-0.716***
	(-1.76)	(-1.73)	(-6.82)	(-6.74)
Immigrant*Post-treat	$ \begin{array}{c} 0.346 \\ (0.97) \end{array} $	$\begin{array}{c} 0.339 \\ (0.95) \end{array}$	0.983^{*} (1.88)	0.972^{*} (1.85)
rage=22	0	0	0	0
	(.)	(.)	(.)	(.)
rage=28	3.191^{***}	3.190^{***}	2.079^{***}	2.076^{***}
	(22.86)	(22.77)	(13.94)	(13.91)
rage=34	4.643^{***}	4.640^{***}	3.659^{***}	3.657^{***}
	(33.43)	(33.16)	(25.03)	(25.02)
rage=40	5.399^{***}	5.397^{***}	4.759^{***}	4.756^{***}
	(34.66)	(34.52)	(27.93)	(27.87)
rage=46	5.725^{***}	5.723^{***}	5.481^{***}	5.478^{***}
	(29.40)	(29.35)	(29.42)	(29.33)
rage=52	5.641^{***}	5.639^{***}	5.364^{***}	5.361^{***}
	(35.96)	(35.82)	(27.61)	(27.57)
rage=58	5.491 ^{***}	5.488 ^{***}	5.430^{***}	5.428^{***}
	(30.96)	(30.92)	(27.23)	(27.21)
rage=64	4.517^{***}	4.516^{***}	4.902^{***}	4.898^{***}
	(24.38)	(24.40)	(19.79)	(19.83)
legth of stay2	-0.0131	-0.0131	-0.0524	-0.0522
	(-0.33)	(-0.33)	(-0.71)	(-0.71)
los2	$ \begin{array}{c} 0.00131 \\ (1.65) \end{array} $	$ \begin{array}{c} 0.00130 \\ (1.64) \end{array} $	0.00153 (1.25)	$ \begin{array}{c} 0.00152 \\ (1.25) \end{array} $
rcohort	-0.000828**	-0.000828**	-0.000715**	-0.000714 ^{**}
	(-2.27)	(-2.27)	(-2.40)	(-2.39)
profession=0	0	0	0	0
	(.)	(.)	(.)	(.)
profession = 1	-1.182	-1.185	-2.660	-2.656
	(-0.69)	(-0.69)	(-1.10)	(-1.10)
profession=2	-6.693***	-6.694***	-8.408***	-8.403***
	(-3.91)	(-3.91)	(-3.52)	(-3.52)
profession=3	2.584 (1.51)	$2.580 \\ (1.51)$	$3.632 \\ (1.51)$	$3.635 \\ (1.51)$
profession=4	2.773	2.769	3.219	3.223
	(1.61)	(1.60)	(1.33)	(1.33)
profession=5	$1.228 \\ (0.71)$	$ \begin{array}{r} 1.225 \\ (0.71) \end{array} $	-0.679 (-0.28)	-0.674 (-0.28)
profession=6	3.579^{**}	3.579^{**}	-3.530	-3.526
	(2.07)	(2.07)	(-1.46)	(-1.46)
profession=7	$0.174 \\ (0.05)$	$0.170 \\ (0.05)$	$ \begin{array}{r} 1.929 \\ (0.74) \end{array} $	$ \begin{array}{r} 1.932 \\ (0.74) \end{array} $
profession=8	-4.156 ^{**}	-4.156**	-4.555	-4.549
	(-2.35)	(-2.35)	(-1.78)	(-1.78)
Married	1.593^{***}	1.595^{***}	0.487^{***}	0.487^{***}
	(21.78)	(21.79)	(8.45)	(8.43)
High sch	4.196^{***}	4.195^{***}	5.850^{***}	5.849^{***}
	(50.57)	(50.60)	(40.38)	(40.42)
1st level tertiary	5.742^{***}	5.740^{***}	6.460^{***}	6.459^{***}
	(70.29)	(70.25)	(76.44)	(76.51)
Postgraduate	7.972^{***}	7.969^{***}	9.580^{***}	9.580^{***}
	(65.87)	(65.87)	(71.18)	(71.30)
resident = urban	0.767^{***}	0.766^{***}	0.769^{***}	0.768^{***}
	(10.08)	(10.05)	(9.42)	(9.38)
ltot_mghbimg		-0.0588 (-1.03)		-0.0897 (-1.24)
Constant	25.93^{***}	26.45^{***}	28.22^{***}	29.01^{***}
	(14.30)	(14.81)	(11.63)	(11.63)
*.dept	Yes	Yes	Yes	Yes
*.annee	Yes	Yes	Yes	Yes
Observations	706807	706614	660137	660003

Table 1.18: Earnings

	(1)	(2)
wage	wage	wage
Immigrant	-0.0515*** (-3.23)	-0.0404* (-1.86)
Treat*Post	0.0387^{***} (3.86)	0.140^{***} (14.14)
Immigrant*Post-treat	-0.0162 (-1.60)	-0.0103 (-0.74)
cohort=1956	0.0706^{**} (2.40)	0.140^{***} (4.21)
cohort=1964	0.0721^{***} (4.33)	0.0591^{***} (2.80)
cohort=1972	-0.0437*** (-2.82)	-0.00396 (-0.13)
cohort=1980	-0.0653*** (-4.30)	-0.0832*** (-4.23)
cohort=1988	-0.0652*** (-3.72)	-0.0792*** (-3.35)
cohort=1996	-0.0843*** (-4.76)	-0.0708*** (-2.82)
cohort=2004	-0.125*** (-8.15)	-0.123*** (-5.55)
cohort=2012	-0.181*** (-7.99)	-0.161*** (-4.89)
Married	0.0576^{***} (31.86)	-0.0700*** (-32.04)
High sch	0.106^{***} (46.36)	0.142^{***} (62.83)
1st level tertiary	0.0853^{***} (57.14)	0.131^{***} (69.72)
Postgraduate	0.165^{***} (40.64)	0.180^{***} (50.66)
Urban	0.00993^{***} (6.41)	0.0226^{***} (12.23)
Constant	8.732*** (93.80)	8.618*** (96.01)
select Married	-0.135*** (-28.13)	$\binom{0.00331}{(0.79)}$
Vie en couple ou non	0.445^{***} (87.80)	0.217^{***} (58.84)
children below 18 years	0.0262^{***} (16.99)	-0.0372*** (-28.39)
Constant	-0.326*** (-110.23)	-0.322*** (-121.54)
/ athrho	-1.294*** (-145.78)	-1.888*** (-223.65)
lnsigma	-0.836*** (-235.16)	-0.462*** (-185.74)
*.dept	Yes	Yes
*.annee	Yes	Yes
Observations	998402	1108905
t statistics in parent	heses	

Table 1.19: Earnings Regression using Heckman selection

t statistics in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

Number of observations	(baseline)	573742			
	Before	After			
Control	280291	-	280291		
Treated	293451	-	293451		
	573742	-			
t-test at period $= 0$					
Variable(s)	Mean Control	Mean Treated	Diff.	$ \mathbf{t} $	$\Pr(T > t)$
active	0.722	0.723	0.00100	0.870	0.384
males	0.497	0.498	0.00100	0.910	0.365
Algeria	0.0260	0.0650	0.0390	71.34	0.0000^{***}
Tunisia	0.00600	0.0170	0.0100	37.30	0.0000^{***}
Morocco	0.0190	0.0440	0.0250	53.97	0.0000^{***}
age	38.04	38.36	0.318	9.280	0.0000^{***}
experience	20.68	20.93	0.252	6.860	0.0000^{***}
cohab	0.650	0.652	0.00300	2.100	0.0354^{**}
married	0.522	0.530	0.00700	5.320	0.0000^{***}
no in house	3.228	3.252	0.0240	6.070	0.0000^{***}
no child18	0.856	0.884	0.0290	9.700	0.0000^{***}
Basic Educ n	0.392	0.397	0.00500	3.990	0.0001^{***}
High sch	0.163	0.158	-0.00500	4.710	0.0000^{***}
Post High sch	0.370	0.366	-0.00500	3.700	0.0002^{***}
Postgraduate	0.0750	0.0790	0.00400	5.850	0.0000^{***}
Urban	0.617	0.613	-0.00400	3.180	0.0015^{***}
Rural	0.383	0.358	-0.0250	19.70	0.0000^{***}
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Table 1.20: Two sample t-test for labor force participation

*** p<0.01; ** p<0.05; * p<0.1

Number of observations	(baseline)	573742			
	Before	After			
Control	280291	-	280291		
Treated	293451	-	293451		
	573742	-			
t-test at period $= 0$					
Variable(s)	Mean Control	Mean Treated	Diff.	$ \mathbf{t} $	$\Pr(T > t)$
employed	0.652	0.652	0	0.220	0.824
sexe	0.497	0.498	0.00100	0.910	0.365
Algeria	0.0260	0.0650	0.0390	71.34	0.0000^{***}
Tunisia	0.00600	0.0170	0.0100	37.30	0.0000***
Morocco	0.0190	0.0440	0.0250	53.97	0.0000^{***}
ag	38.04	38.36	0.318	9.280	0.0000^{***}
exp	20.68	20.93	0.252	6.860	0.0000^{***}
cohab	0.650	0.652	0.00300	2.100	0.0354^{**}
married	0.522	0.530	0.00700	5.320	0.0000***
no inhouse	3.228	3.252	0.0240	6.070	0.0000^{***}
no child18	0.856	0.884	0.0290	9.700	0.0000^{***}
Basic Educ n	0.392	0.397	0.00500	3.990	0.0001^{***}
High sch	0.163	0.158	-0.00500	4.710	0.0000^{***}
Post Highsch	0.370	0.366	-0.00500	3.700	0.0002^{***}
Postgraduate	0.0750	0.0790	0.00400	5.850	0.0000***
Urban	0.617	0.613	-0.00400	3.180	0.0015^{***}
Rural	0.383	0.358	-0.0250	19.70	0.0000***

Table 1.21: Two sample t-test for employment rates

*** p<0.01; ** p<0.05; * p<0.1

	(1)	(2)	(3)	(4)
	Active	Active	Employed	Employed
	Male	Female	Male	Female
Algeria	-0.430^{***}	-0.614^{***}	-0.781***	-0.910^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Tunisia	-0.408***	-0.660^{***}	-0.766^{***}	-0.937^{***}
	(0.001)	(0.000)	(0.000)	(0.000)
Morocco	-0.328***	-0.567^{***}	-0.668***	-0.904***
	(0.000)	(0.000)	(0.000)	(0.000)
Treated dept	-0.209***	-0.0100	-0.285***	0.0328
	(0.000)	(0.727)	(0.000)	(0.240)
Post treatment	0.0416^{***} (0.002)	0.257^{***}	-0.130*** (0.000)	0.155***
Treat*Post	0.0181**	-0.00456	0.0246^{***}	-0.00672
Algerian*treat*post	0.0656	0.122***	0.0571	0.166***
Tunisian*treat*post	0.0302	0.0808	0.0651	0.145*
Moroccan*treat*post	-0.0212	-0.0234	0.0172	0.111**
Age=28	(0.697)	(0.590)	(0.701)	(0.012)
Age=34	(0.000)	(0.000)	(0.000)	(0.000)
Age=40	(0.000)	(0.000)	(0.000)	(0.000)
	1.980^{***}	1.823^{***}	1.689^{***}	1.635^{***}
Age=46	(0.000)	(0.000)	(0.000)	(0.000)
	1.849***	1.768^{***}	1.651^{***}	1.755^{***}
Age=52	(0.000)	(0.000)	(0.000)	(0.000)
	1.612^{***}	1.464^{***}	1.536^{***}	1.716^{***}
Age=58	(0.000)	(0.000)	(0.000)	(0.000)
A ==== 6.4	(0.000)	(0.000)	(0.000)	(0.000)
Age=64	(0.000)	(0.000)	(0.000)	(0.000)
Length of stay	(0.0222^{***})	(0.0163^{***})	(0.0159^{+++}) (0.002)	(0.0197^{***})
Length of stay sq	-0.000281*** (0.005)	-0.000130 (0.158)	$\begin{array}{c} 0.0000702 \\ (0.433) \end{array}$	-0.0000304 (0.744)
cohort=1956	$ \begin{array}{c} 0.102 \\ (0.379) \end{array} $	$\begin{array}{c} 0.172 \\ (0.130) \end{array}$	-0.314*** (0.003)	-0.134 (0.237)
cohort=1964	0.0764	0.0668	-0.0999	-0.117
	(0.343)	(0.369)	(0.143)	(0.112)
cohort=1972	0.167^{**}	-0.0677	-0.0370	-0.311***
	(0.016)	(0.287)	(0.519)	(0.000)
cohort=1980	-0.0273	-0.0222	-0.155***	-0.224***
	(0.674)	(0.674)	(0.004)	(0.000)
cohort=1988	-0.0872	-0.0997^{*}	-0.205^{***}	-0.317^{***}
	(0.182)	(0.066)	(0.000)	(0.000)
cohort=1996	-0.135^{**}	-0.0335	-0.205^{***}	-0.177^{***}
	(0.045)	(0.552)	(0.000)	(0.001)
cohort=2004	-0.137**	-0.326***	-0.180***	-0.419***
	(0.048)	(0.000)	(0.004)	(0.000)
cohort=2012	-0.301^{***}	-0.554^{***}	-0.310^{***}	-0.582^{***}
	(0.001)	(0.000)	(0.000)	(0.000)
Married	0.387^{***}	-0.0816^{***}	0.476^{***}	-0.0992^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
High sch	0.198^{***}	0.330^{***}	0.319^{***}	0.452^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
1st level tertiary	0.448^{***}	0.453^{***}	0.449^{***}	0.485^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Postgraduate	0.489*** (0.000)	0.504^{***} (0.000)	0.575*** (0.000)	0.645*** (0.000)
Urban	-0.101***	-0.0770***	-0.153***	-0.0730***
size of the household	0.000591	-0.0845***	(0.000)	(0.000)
children below 18 years	-0.0120***	-0.186***		
Constant	-0.323***	-0.380***	-0.460***	-1.112***
*.dept	(0.000)	(0.000)	(0.000)	(0.000)
	Yes	4 Yes	Yes	Yes
*.annee	0 Yes	4 Yes	Yes	Yes

 Table 1.22: Heterogeneity by country of Origin

	(1) Active Male	(2) Active Female	(3) Employed Male	(4) Employed Female
Imig less than 5yrs stay	-0.314^{***} (0.001)	-0.657^{***} (0.000)	-0.760^{***} (0.000)	-0.940^{***} (0.000)
Imig greater than 5yrs stay	-0.270^{**} (0.016)	-0.337^{***} (0.000)	-0.641*** (0.000)	-0.713^{***} (0.000)
Treated dept	-0.210*** (0.000)	-0.00966 (0.737)	-0.286*** (0.000)	0.0332 (0.233)
Post treatment	0.0411^{***} (0.002)	0.257^{***} (0.000)	-0.131^{***}	0.155^{***} (0.000)
Treat*Post	0.0182^{**} (0.029)	-0.00460 (0.519)	0.0248^{***} (0.001)	-0.00675 (0.325)
Imig less than 5yrs stay*treat*post	-0.0890 (0.302)	0.0821 (0.273)	0.0682 (0.376)	0.110
Imig greater than 5yrs stay*treat*post	0.0386 (0.316)	0.0577^{*}	0.0334 (0.295)	0.146^{***}
Age=28	1.406^{***}	1.227***	1.207***	1.235*** (0.000)
Age=34	1.996***	1.638***	1.639***	1.499*** (0.000)
Age=40	1.980***	1.823***	1.689***	1.635***
Age=46	1.849***	1.768***	1.650***	1.755***
Age=52	1.612***	1.464***	1.536***	1.716***
Age=58	0.861***	0.883***	0.928***	1.326***
Age=64	-0.658***	-0.349***	-0.486***	0.220***
Length of stay	(0.000) 0.0142*	-0.00190	0.00998	0.00607
Length of stay sq	(0.061) -0.000171	(0.754) 0.000134	(0.119) 0.000161	(0.329) 0.000166
cohort=1956	(0.156) 0.0864	0.129	(0.127) -0.347***	-0.163
cohort=1964	(0.458) 0.0769	(0.257) 0.0969	(0.001) -0.123*	(0.150) -0.0979
cohort=1972	(0.337) 0.185^{***}	(0.187) -0.0312	(0.068) -0.0268	(0.178) -0.284 ^{***}
cohort=1980	(0.008) -0.0103	(0.625) 0.00640	(0.642) -0.137**	(0.000) - 0.203^{***}
cohort=1988	(0.874) -0.0908	(0.904) -0.102*	(0.010) -0.199***	(0.000) - 0.320^{***}
cohort=1996	(0.165) -0.164 ^{**}	(0.059)-0.0750	(0.000) -0.216***	(0.000) - 0.212^{***}
cohort=2004	(0.015)	(0.186)	(0.000)	(0.000)
cohort=2012	(0.023)	(0.000)	(0.002)	(0.000)
2012	(0.002)	(0.000)	(0.000)	(0.000)
Married	(0.000)	-0.0814	(0.000)	-0.0992
High sch	0.198*** (0.000)	0.330*** (0.000)	0.319*** (0.000)	0.452*** (0.000)
1st level tertiary	0.448^{***} (0.000)	0.453^{***} (0.000)	0.449^{***} (0.000)	0.485^{***} (0.000)
Postgraduate	0.489^{***} (0.000)	0.504^{***} (0.000)	0.576^{***} (0.000)	0.645^{***} (0.000)
Urban	-0.101*** (0.000)	-0.0770*** (0.000)	-0.153^{***} (0.000)	-0.0730^{***} (0.000)
size of the household	$\begin{array}{c} 0.000635 \\ (0.812) \end{array}$	-0.0844^{***} (0.000)		
children below 18 years	-0.0120^{***} (0.002)	-0.187^{***} (0.000)		
Constant	-0.322*** (0.000)	-0.381*** (0.000)	-0.459^{***} (0.000)	-1.112^{***} (0.000)
*.dept	Yes	Yes	Yes	Yes
*.annee fixed effects N	Yes	Yes	Yes	Yes

Table 1.23: Heterogeneity by length of stay

 $\begin{array}{c} p \text{-values in parentheses} \\ * p < 0.1, ** p < 0.05, *** p < 0.01 \quad 65 \end{array}$

	(1) Active Male	(2) Active Female	(3) Employed Male	(4) Employed Female
Native youth less than 25 yrs	-0.680^{***}	-0.553^{***}	-0.519^{***} (0.000)	-0.459^{***} (0.000)
Young immigrant less 25	-0.209^{**} (0.029)	0.140 (0.112)	-0.482*** (0.000)	-0.413^{***} (0.000)
Elderly immigrant older 25	-0.512^{***}	-0.820*** (0.000)	-0.830*** (0.000)	-1.026^{***}
Treated dept	-0.210***	-0.0113	-0.288***	0.0304
Post treatment	0.0412***	0.257***	-0.134***	0.152***
Treat*Post	0.0165**	-0.00443	0.0239***	-0.00654
Young immigrant*treat*post	0.0337	-0.225***	0.170*	0.0484
Elderly immigrant $treat post$	0.0290	0.0867***	0.0332	0.149***
Age=28	(0.437)	(0.003)	(0.276) 0.886***	(0.000) 0.942***
Age=34	(0.000) 1.338^{***}	(0.000) 1.119^{***}	(0.000) 1.130^{***}	(0.000) 1.053^{***}
Age=40	(0.000) 1.326^{***}	(0.000) 1.308^{***}	(0.000) 1.182^{***}	(0.000) 1.190^{***}
Age=46	(0.000) 1.194^{***}	(0.000) 1.246^{***}	(0.000) 1.144^{***}	(0.000) 1.311^{***}
Age=52	(0.000) 0.956***	(0.000) 0.936***	(0.000) 1.029***	(0.000) 1 272***
Ago=59	(0.000)	(0.000)	(0.000)	(0.000)
A == -64	(0.000)	(0.000)	(0.000)	(0.000)
Age=04	(0.000)	(0.000)	(0.000)	(0.000)
Length of stay	(0.000)	(0.000)	(0.000)	(0.000)
Length of stay sq	-0.000330*** (0.001)	-0.000229** (0.011)	$ \begin{array}{c} 0.0000225 \\ (0.797) \end{array} $	-0.0000824 (0.371)
cohort=1956	$\begin{array}{c} 0.0861 \\ (0.458) \end{array}$	$ \begin{array}{c} 0.167 \\ (0.141) \end{array} $	-0.341*** (0.001)	-0.139 (0.217)
cohort=1964	$\begin{array}{c} 0.0594 \\ (0.455) \end{array}$	$\begin{array}{c} 0.0730 \\ (0.320) \end{array}$	-0.136** (0.042)	-0.116 (0.112)
cohort=1972	0.165^{**} (0.017)	-0.0758 (0.232)	-0.0415 (0.467)	-0.315^{***} (0.000)
cohort=1980	-0.0263 (0.684)	-0.0290 (0.581)	-0.152^{***} (0.004)	-0.227*** (0.000)
cohort=1988	-0.111* (0.088)	-0.120^{**} (0.025)	-0.219*** (0.000)	-0.328*** (0.000)
cohort=1996	-0.154^{**} (0.021)	-0.0435 (0.438)	-0.217^{***} (0.000)	-0.183 ^{***} (0.001)
cohort=2004	-0.138^{**} (0.041)	-0.299^{***} (0.000)	-0.175^{***} (0.005)	-0.404^{***} (0.000)
cohort=2012	-0.286*** (0.001)	-0.522^{***} (0.000)	-0.300*** (0.000)	-0.564^{***} (0.000)
Married	0.368^{***} (0.000)	-0.103*** (0.000)	0.466^{***} (0.000)	-0.114*** (0.000)
High sch	0.214^{***} (0.000)	0.337^{***} (0.000)	0.332^{***} (0.000)	0.458^{***} (0.000)
1st level tertiary	0.451^{***} (0.000)	0.452^{***} (0.000)	0.450^{***} (0.000)	$0.485^{***} \\ (0.000)$
Postgraduate	$\begin{array}{c} 0.484^{***} \\ (0.000) \end{array}$	0.505^{***} (0.000)	0.571^{***} (0.000)	0.643^{***} (0.000)
Urban	-0.0987^{***} (0.000)	-0.0748^{***} (0.000)	-0.154*** (0.000)	-0.0726^{***} (0.000)
size of the household	0.0114^{***} (0.000)	-0.0754^{***} (0.000)	·	·
children below 18 years	-0.0224*** (0.000)	-0.201*** (0.000)		
Constant	0.319***	0.145***	0.0576^{*}	-0.654^{***}
*.dept	Yes	Yes	Yes	Yes
*.annee	Yes	Yes	Yes	Yes
N	110610166	1160667	1106101	1160667

Table 1.24: Heterogeneity by age group

Chapter 2

Remittances and Natural disasters

Abstract

The literature on the impact of natural disasters on remittances is filled with mixed evidence, with identification remaining as a key challenge. In this study, we aim at addressing this identification problem by using a rare monthly data on remittance outflows and perform a non-parametric event study to flexibly characterise and document the dynamic response of remittances to natural disasters over a 12 month horizon. We use a novel and rich panel data set of monthly remittance flows from Italy to 81 developing countries for the period 2005 to 2015. We find that monthly remittance flows significantly responds to the occurrence of natural disasters in the migrants home country albeit with a lag and that remittances also plays a role in mitigating the impact of macroeconomic shocks such as the cyclical fluctuations in the terms of trade. We find A heterogenous response to disasters depending on the size of the immigrant population, country's level of development, the nature and timing of the disaster. The study also finds strong evidence that the macroeconomic condition of the host country as well as the concentration and location of immigrants within the host country to be significant determinant of remittance flows from Italy and to a lesser extent determinants of post-disaster remittance flows from Italy.

2.1 Introduction

Recently, scholars have been interested in understanding if remittances play any role in mitigating the effects of natural disasters. While some scholars find that remittances increases in response to the occurrence of a disaster and contributes positively toward disaster preparation (see for example David (2010), Mohapatra et al. (2012), Bettin and Zazzaro (2018)), others on the contrary do not find any evidence that remittances responds to disasters (see for example, Lueth et al. (2006), Bettin et al. (2015)). The reason for the disparate findings range from using different methodologies, different sample compositions, focusing on different time periods as well as the different type of disasters studied.

Despite these series of attempts made to identify the impacts of disasters on remittances, identification have remained a key challenge. This could be largely attributed to the nature of the data used in conducting such studies. Almost all of the previous studies in this literature uses annual data which makes it quite challenging to infer causality. For instance, it is difficult to attribute an increase in the size of remittances in a given year to the occurrence of a disaster in the early part of the year, say in January. Any effect of the disaster is likely to be confounded by many other factors that may not be easy to control for making it difficult to isolate the effect of disasters from other events and thus to make a claim about causality.

Secondly, the use of annual data masks any potential reallocation effects that may take place within the year. For instance, immigrants may reallocate future remittances to the current period in response to a disaster, but due to their limited financial ability, they compensate for this current increase by reducing future remittances such that annual remittances remains almost unchanged. Studies using annual data will fail to capture this reallocation effect which may be relevant in mitigating the effects of the disaster and thus wrongly conclude that remittances do not respond to disasters. Similar arguments could be made if disasters are somehow anticipated and that migrants remit more before the disaster to minimise the potential loses from such disasters. Indeed a descriptive analysis by **Bragg et al.** (2018) provide some suggestive evidence that most of the increase in remittances is observed in the quarter in which the disaster occur and rarely a significant annual increase is observed. This highlights a potential need for a more systematic investigation using higher frequency data to better understand the behaviour of remittances in the aftermath of disasters.

Thirdly, previous studies due to the nature of data used have mostly focused on the magnitude of the response, thus ignoring an arguably very important dimension of the response to disaster. That is, the timing of the flow of remittances. Intuitively, one may expect that depending on the type of the disaster, the timing of the response may be very crucial to mitigate the devastating impact of disasters. Therefore, this study in addition to attempting to provide a better identification of the impact of disasters on remittances, we also attempt to clearly document the timing of the response of these flows as well as to identify the main channels through which disasters affect remittances.

The study focuses on a panel of 81 developing countries for the period 2005 to 2015. It uses monthly remittance outflow data from Italy obtained from the Bank of Italy and monthly disaster data from the EM-DAT CRED database as well as some macroeconomic data from the world bank, IMF and Italian statistical institute.

We perform a non-parametric event study which allows us to flexibly characterise the dynamic response of remittances to natural disasters over a 12 month horizon. We use three alternative specifications mainly relating to how our key dependent variable is constructed and the assumptions we make about the effect of events outside our estimation window. First, we define our disaster variable to only include disasters occurring between 2006 and 2014 and make the assumption that the response to disasters diminishes to zero outside our 12 month window. Since the occurrence of disasters are random, such a strategy should not bias our results once we control for time and country fixed effects. Secondly, following recent advances in the literature on multiple event studies by Sun and Abraham (2020), Schmidheiny and Siegloch (2020) among others, we define our disasters on remittances to remain constant outside the chosen effect window. Finally, noting that the flexibility of the dynamic response may be inefficient in the case that the parameter estimates are not significantly different from each other, we aggregate the pre and post disaster coefficient to increase the power of our estimates and to allow for more controls.

This study contributes to the existing literature in the following ways; firstly, it is one of the first study to use monthly remittance data in this literature. The use of monthly remittance data coupled with an event study approach allows for better identification of the impact of disasters on remittance flows and to document the timing of the response of these flows. Additionally, this study extends the existing literature on the determinants of remittances by being the first that attempts to incorporate how the degree of concentration of immigrants and their place of residence within the host country affect remittance outflows and how they affect the response of remittances to disasters.

This study finds that per-capita monthly remittance flows plays a significant role in mitigating the effects of disasters and other economic shocks in the migrants origin country in line with previous findings by David (2010), Balli and Rana (2015) and Bettin et al. (2018). Remittance flows from Italy increase by about 2 percent in response to the occurrence of natural disasters in the immigrants origin country. This estimated response is robust to various alternative specifications such as how the disaster measure is constructed, controlling for past and future disasters, as well as controlling for other shocks occurring in the origin country and the macroeconomic characteristics of the host country, using alternative measures of disasters and making different assumptions concerning the effect of disasters outside our effect window. We find that the estimated response is mainly driven by the significant response to disasters occurring in upper middle income countries and in countries with a larger stock of immigrants in Italy. The response is higher for events occurring prior to the global financial crises, and when separated by disaster type, for climatic and meteorological disasters.

There is also an observed difference in the timing of the response based on the nature of the disaster. When we distinguish between sudden-occurring and slow-occurring disasters, we find a swift response to sudden disasters mostly within the first three months after the disaster occurred compared to slow disasters which responds with a lag of about three months. The size of the response to slow-occurring disasters is relatively larger and lasts for a longer period compared to sudden disasters. Our findings also confirms the results of Bettin et al. (2014) on the counter-cyclical role of remittances in reaction to a terms of trade shock.

We also find evidence that higher concentration of immigrants is associated with smaller amount of remittance flows, at least through formal channels. Similarly, having a larger share of the diaspora residing in Northern Italy is associated with smaller amount of remittances. This results seems to be driven by the higher concentration of immigrants in the North of the country that could either increase competition on the labour market thereby having negative effects on the income levels of immigrants or allow for the emergence of informal means of remitting.

Contrary to previous studies, this study do not find remittances from Italy to be resilient to adverse economic events in the host country such as the global financial crises, the subsequent euro-zone crises, and or a worsening of the aggregate economic conditions in the host country. Furthermore, we also find that the response of remittances to disasters are affected to some extent by the existing macroeconomic conditions at the time of the occurrence of the disaster as well as the concentration and location of the immigrants within the host country. All our results are robust to controlling for additional factors as well as using alternative measures of disaster and clustering the standard errors at the origin country level to allow for correlation within a country overtime.

The paper proceed as follows, section 2 provides a brief review of the literature, section 3 explains the empirical framework used in estimating the effects of shocks on remittances, section 4 provides a description of the data and outlines the sources of data and section 5 provides the result whilst section 6 concludes the analysis.
2.2 Literature review

The literature on remittances and natural disasters is quite extensive. At a macro level is the literature on the impact of disasters and other economic shocks on economic growth and the response of the various components of GDP. Some studies further investigate the response of aggregate financial flows such as foreign aid, foreign direct investment and remittances among others in the aftermath of a disaster as well as how these flows are correlated with the business cycles of recipient countries. Furthermore, at a micro level, earlier studies have been interested in the different motives for remitting and the factors affecting remittance flows. More recent studies have examined the impacts of economic and natural shocks on emigration and remittance flows linking it with the various motives of remitting.

This literature review is organised as follows: first I summarise the part of the literature that discusses the macroeconomic impacts of natural disasters and other shocks on economic growth as well as how the various component of GDP are affected. Next, I summarise the literature on the response of capital and other financial flows to natural disasters and economic shocks as well as how these flows are correlated with the business cycles of recipient countries. Finally, I conclude this section by reviewing the more closely related literature to my work, that is the relationship between remittances and natural disasters.

Macroeconomic consequences of disasters

Several authors find a significant negative effect of disaster on economic growth (see Nov (2009). Raddatz (2009), Berlemann and Wenzel (2018), Bluedorn (2005)). For instance, Noy (2009) estimate a 9 percent reduction in GDP growth from a one standard deviation increase in the disaster index for developing countries particularly for small developing economies compared to a less than 1 percent reduction for developed countries. He highlight the large impacts might be due to the disruptions in labour, financial and output markets and the resultant diversion of government resources. On the other hand, the ability of developed countries to counter this effect through fiscal and monetary policy has been mostly credited for the low impact of disaster in developed countries. Berlemann and Wenzel (2018) instead focus only on hurricanes and also finds a significant negative cumulative effect of hurricanes on growth, about half of the former's finding. While Raddatz (2009) estimate a 0.6 percent reduction in GDP per-capita from a climate related disaster. Besides the cross-sectional studies cited above, some country case studies looking at specific events also find similar results. For instance, Heger and Neumayer (2019) focused on the impact of the 2004 tsunami on the long term economic growth of the most affected province of Indonesia (about 90% of all damages) and find that affected provinces experienced a higher growth path after the disaster. They find that the disaster significantly reduced economic activity for affected provinces relative to non-affected provinces by about 8% in the year of the disaster.

However, the evidence on the effects of disasters on economic growth is mixed. For instance, Cavallo et al. (2012) focusing on only large disasters¹ and conducting a counterfactual analysis using synthetic control methods did not find strong evidence that large disasters have a significant negative effect on growth². Others even find subsequent positive effects of disasters. For instance, Skidmore and Toya (2002) studying the long term effects of natural disasters using cross sectional data for the period 1960 to 1990 and conditioning on controls such as fertility, education, investment and government spending, finds that climatic disasters have a statistically positive significant effect on real economic growth. Likewise, Heger and Neumayer (2019) find that output quickly recovered after the disaster (within 2 years) and have since set on a higher growth path between 3% and $6\%^3$. Berlemann and Wenzel (2018) put forward several possible explanations for the mixed results derive from various studies on the growth effects of disasters. They argues that among other reasons; treating all climatic disasters as homogeneous might be one possible explanation for the disagreement in findings, since disasters may have a heterogeneous effect on economic development. They also cite problems associated with measuring severity of disasters, methodological issues and the fact that the effect of a disaster may depend on a country's level of development.

To understand how the various component of GDP respond to a shock, scholars use a national accounting approach to disentangle these effects. They generally find that at the strike of a disaster, exports fall while imports and government expenditure increase (Mohan et al. (2018)). However, the evidence on the response of consumption and investment to disaster is mixed. For instance, while Bluedorn (2005) and Mohan et al. (2018) who both focus on small countries in the Caribbean and Central America that are prone to hurricane strike finds gross investment to responds positively and consumption to respond negatively to hurricanes, Noy (2009) studying a broader range of disasters beyond hurricanes and a larger set of countries for around the same period find only a weak evidence of an increase in investment after a disaster. These results he said might capture both the fact that after a disaster, reconstruction investment increases but other investments may decrease due to expectation about future disasters.

Other factors such as institutional strength, higher per-capita income, a bigger government proxied by government consumption as percentage of GDP, a higher level of exports and being located in the tropics are associated with lower macroeconomic cost. While a higher level of illiteracy (proxy for human capital) is associated with higher macroeconomic cost. Noy (2009) explains that stronger institutions are more efficient in providing interventions after a disaster and larger governments are more able to mobilise resources for reconstruction purposes. Like-

 $^{^1\}mathrm{The}$ study further restrict the analysis to the three most common disasters; earthquakes, floods, and wind-storms.

 $^{^{2}}$ The author define large disasters as events in the 99th, 90th, and 75th percentiles of the world distribution of the number of people killed relative to a country's population. It should however be noted that relative to other studies, this study considers only a small number of disaster events. For instance, the total number of events considered even at the 75th percentile is just 22.

 $^{^{3}}$ However, this quick recovery and subsequent higher growth path is heavily attributed to the increase in government spending and the large foreign aid inflows used to finance reconstruction activities.

wise, more open economies are less affected by the negative demand shocks and also have a higher ability in attracting capital inflows to help in the reconstruction process.

One may arguably conclude that the varying response in timing and impact on the various GDP components as well as the different types of disasters and the relatively small and concentrated nature of certain disasters may explain why it may be difficult to find clear and large aggregate impact on GDP⁴. Importantly, the overall macroeconomic costs of disasters may also hinge on the context and the level of attention given to it by both governments and international organisations.

Financial flows and natural disasters

Another strand of literature related to this study is the response of financial flows to economic shocks and natural disasters as well as their relationship with the business cycle. These flows have been identified as an important channel through which disasters may affect the economy. They present a potential channel that could help mitigate the adverse effects of such disastrous events through their consumption smoothing role and their ability to mobilise funds in the reconstruction process. Evidence on the response of foreign aid is a mixed one. A study by David (2010) covering 78 countries for the period 1970 to 2005 estimated the response of various capital flows by specifying a dynamic panel VAR model conditioning on the real interest rate differential, income differential and the exchange rate. Categorising disasters into climatic, human and geological disasters, the author did not find robust evidence that foreign development aid increases in response to disasters. The author only find aid flows to respond to geological disasters with a two year lag. On the other hand, Becerra et al. (2014) conducting an event study analysis with data on bilateral aid flows from 44 donor countries to 165 aid recipient countries for the period 1970 to 2008 and focusing only on large disasters finds that aid flows responds positively to disasters. They estimate that aid flows increases by about 8 percent in the year of the disaster and about 20 percent the year after the disaster and then declines from the second year onward but they do not return to their pre-disaster levels for at least 6 years after. The response of these flows are small compared to the economic damage that disasters inflicts on these countries and is also very volatile and closely mimics the economic conditions of the sending countries⁵. An exception to this is the case of the province of Aceh in Indonesia which experienced one of the largest reconstruction effort financed by foreign aid amounting to 7.7 billion USD, about 150 percent of the total damages (Heger and Neumayer (2019)).

However, changes in aggregate aid inflows may hide important reallocation of aid that may potentially take place when a disaster strikes. Donor partners may reallocate aid from other sectors to provide relief assistance to disaster affected communities which may not be obvious

⁴For instance, Heger and Neumayer (2019) highlights that the economy of the province of Aceh in Indonesia is relatively too small compared to the entire Indonesian economy.

⁵For instance in the study by Becerra et al. (2014), the average aid surge as a percentage of GDP was about 0.25 percent whilst the average economic damages caused by a disaster was about 5 percent of GDP.

from the data. Nonetheless, the fact remains that the response of foreign aid is mostly not immediate.

Deryugina (2017) conducting an event study analysis for hurricanes occurring in the U.S between 1969 and 2012, find that non-disaster government transfers in the form of unemployment benefits and public medical payments increase significantly and persistently in the ten year period after a county is hit by a hurricane. This estimated increase ranges between 1.3 percent to 3.9 percent of its mean capita. Similarly, (David (2010)) find that other financial flows such as bank lending decreases immediately in response to disasters. Though the estimated effects are only statistically significant for climatic disasters and human disasters, 0.8 percent and 0.1 percent respectively. Net equity flows on the other hand increases on impact in response to a climatic disaster but this response is short-lived as the coefficient becomes statistically insignificant in subsequent periods. Though the estimated effect for geological disasters is positive it is not statistically significant.

Remittances, economic shocks and natural disasters

A more closely related literature to this study is the one investigating the response of remittances to economic shocks and natural disasters. Remittances, unlike other financial transfers are less volatile and goes directly into family incomes bearing an immediate and direct effect on the livelihoods of receiving households (Skidmore and Toya (2002)). Remittances constitute a major source of income for many households in developing countries. For instance, in Jamaica, remittances as a percentage of total annual expenditure ranges from 7 to 26 percent for the highest and lowest decile respectively. Its proportion of total support received is even much higher ranging from 50 percent for the top decile to as much as 87 percent for the lowest decile (Kirton (2005)).

Several studies find a positive response of remittances to both economic shocks and natural disasters. For instance, Yang (2008) studied the effect of an exchange rate shock on the propensity to remit and how these remittances impact on household outcomes in migrants origin countries. The paper solely focus on Filipino migrants in different destinations around the time of the Asian financial crises in 1997 and finds that a 10% increase in the domestic currency per unit of foreign currency increases remittances by 6%. Similarly, Bettin et al. (2015) finds that remittances are counter-cyclical to the business cycles of recipient countries with their elasticity estimates ranging between -1.87 for the model with full controls to -3 in the parsimonious model. The authors use a rich panel dataset on bilateral remittances between 103 Italian provinces and 79 developing countries for the period 2005–2011. They apply a fixed effect poisson estimator and condition their analysis on the trend and cycle of GDP, the stock of immigrants, population size, level of financial development and foreign aid. Their findings reveal that a 1% decline in cyclical output translates to an increase in remittances between \$13 million for the Philippines to \$263 for Dominica. Similarly, they also find annual remittances significantly increase in response to a deterioration in the terms of trade, about 0.5% for every 1% decline in terms of trade. Both the estimated effects for the cycle and terms of trade increase with an increase in the share of newly arrived immigrants. Balli and Rana (2015) examine the role of remittances as a source of insurance (risk sharing) against domestic output shocks. Their estimates reveal the degree of a country's output smoothing via remittances to be about 5 percent and that the average co-movement between a country's output and consumption declines from 55 percent to 46 percent once remittance inflows are added to consumption. This suggests a large increase in consumption smoothing via remittances⁶. However, the existing empirical evidence on this is also inconclusive. Others suggest the opposite, that is remittances may be pro-cyclical particularly if they are mainly driven by investment motives (see Lueth et al. (2006), Yang (2008)).

Dridi et al. (2019) use country level data for 35 sub-Saharan African (SSA) countries for the period 2011-2015 and data on remittance inflows, consumption patterns and input-output linkages for each country to quantify the effect of remittance inflows across economic sectors. They find that in diversified economies whose production structures are integrated and its sectors highly interlinked, if remittances are spent in sectors which have a strong link with other sectors of the economy, this will lead to growth in demand for output of both the affected sectors and others linked to it. This generates employment and stimulate investment thus benefiting the whole economy.

Several studies have been interested in understanding the relationship between remittances and natural disasters. While some find evidence that remittances increase after a disaster, others do not find any relationship between the two. David (2010) finds a 0.1 percent significant contemporaneous increase in remittance flows for a one standard deviation increase in the incidence of climatic disasters and this increase is statistically significant even after a year. Similarly he find that remittances respond positively to geological disasters and this effect is much more persistent. However he does not find a statistically significant response for human disasters such as famines. Mohapatra et al. (2012) using data for 129 countries for the period 1970 to 2006 estimates a panel fixed effects model and finds evidence that remittance increase in response to disasters. For countries with a 10% emigrant stock relative to its population, remittances increase by about 0.5% of GDP for every 1% increase in the population affected by a disaster and the effect gets much larger for countries with a larger stock of migrants abroad. Similarly, Bettin and Zazzaro (2018), use a two-step GMM estimator conditioning on the stock of the immigrant population, GDP per-capita, official development aid and an indicator for extreme whether events for a sample of 98 countries covering the period 1990 to 2010. They find that remittance flows respond positively to the occurrence of natural disasters, and also

 $^{^{6}}$ Though Balli and Rana (2015) advised this results to be interpreted with caution due to problems associated with consumption data

contribute to disaster preparedness in the sense that they increase with past number of natural disasters. However, the study by Bettin et al. (2014) which uses a more extended model that controls for many other potential shocks that may affect the flow of remittances such as the cycle and trend of GDP, the occurrence of armed conflicts as well as the terms of trade⁷ did not find any evidence that there is a statistically significant increase in remittances in response to a disaster. The study however is limited to remittances from Italy to the rest of the world. Similarly, an earlier study by Lueth et al. (2006) estimating a gravity model for remittances and using a different dataset did not find any evidence that remittances responds to disasters in origin country regardless of the measure of natural disaster used.

This study is similar to the study by Bettin et al. (2014) in many ways; for instance this study also uses the same dataset of remittance outflows from Italy, consider a similar set of countries and condition on a similar set of controls. However, the two also differs in many important ways. First, this study uses monthly aggregate data instead of annual provincial data. Secondly, this study considers a relatively longer period from 2005 up to 2015 instead of 2011. This makes it possible to also investigate the effect of the euro zone crisis that followed the global financial crises. Thirdly, this paper uses a different methodology that is better able to document the flow of remittances around the time the disaster occurs. This paper adopts an event study approach similar to Deryugina (2017) and Becerra et al. (2014) that allows for the estimation of both the magnitude and timing of the response.

Several studies also find that the financial sector plays a crucial role in facilitating remittance flows and mitigating the macroeconomic effects of disasters (see Misati et al. (2019), Bettin et al. (2018)). Few studies have also studied the factors affecting the response of remittances to disasters and or other shocks. Among them, Mohapatra et al. (2012) finds that countries with a larger emigrant stock relative to its population receive higher remittances as a share of GDP in response to an increase in the share of its population affected by a disaster. Similarly Bettin et al. (2014) also find that the counter-cyclical role of remittances to economic shocks to be higher for countries with a relatively larger share of newly arrived immigrants residing in a province. Bettin and Zazzaro (2018) on the other hand finds proxies for financial development (private credit from banks and bank deposits to GDP) to have a positive and significant effect on remittances flows in the aftermath of a disaster implying that countries with a less developed financial sector rely on remittances as a substitute for local finance in the reconstruction process⁸. The findings of the study by Lueth et al. (2006) also supports the theory that financial development in home country is associated with higher remittance flows.

At a micro level, a set of studies have examined the impacts of economic and natural shocks on emigration and remittance flows. Berlemann and Steinhardt (2017) provide a survey of the

⁷Though they do not control for other extreme whether events such as extreme temperature or rainfall. ⁸A well developed financial sector allows for more access to credit that could facilitate the recovery process from the disaster.

empirical literature on how climatic factors, climate-induced hazards and natural disasters affect domestic and international migration flows. One of the transmission channels identified through which disasters might induce migration is the labour channel, the fall in output, productivity, wages and corresponding rise in unemployment leads to a rise in wage differential between places and thus inducing migration. ⁹ Attzs (2008), focusing on small island development states of the Caribbean, explores the poverty-disaster nexus. She highlights that the unsustainable livelihood practices of the poor¹⁰ increases their vulnerability and triggers the occurrence of natural disasters that worsens their level of material poverty. She outlines that migrating in response to disasters may in fact increase the severity of future disasters since emigration lowers the economic opportunities in the area leading to lower reconstruction through infrastructural investment which may amplify effect of future disasters. However, she also cite the significant role of remittance flows to the central America and the Caribbean in smoothing consumption of affected families.

Earlier studies have also focus on the motives for remitting, distinguishing between altruistic motive, investment motive, debt repayment and securing of inheritance rights, See Rapoport and Docquier (2005) for a good survey of the literature on the motives for remitting. Lueth et al. (2006) find support for the altruism motives but did not find evidence for the profit driven motive¹¹. Hoddinott (1994) on the contrary, using household data for rural Kenya finds parents wealth and credibility of threats to exclude migrants from sharing their wealth to have positive influence on amount of remittances received pointing to inheritance motives for remitting.

Although some of the existing evidence indicate that remittance flows positively respond to natural disasters, only little is known about the factors that influence the response of remittances to disasters. Additionally, the timing of the response may be critical particularly in countries where government response and or humanitarian aid is not immediate.Furthermore, the literature excessively relies on annual data ignoring the dynamics that may occur within the year. A descriptive case study by Bragg et al. (2018) focus on 12 countries that have experienced major sudden disasters for the period 2004 to 2014. The authors carried out separate event study analysis for each country. Using quarterly data, they observe that remittances significantly increase in the quarter in which the disaster occurred and that this increase tend to be larger than the average rise in remittances for the entire period. However, they note that this increase is likely to be compensated by a future decline in subsequent quarters. On the other hand, using the aggregated annual data, they observe the annual increase in remittances in the year of the disaster to be less than the average annual increase over the entire period.

 $^{^{9}}$ Lueth et al. (2006) use bilateral remittance data for about 200 country pairings for the period 1980 to 2004 to estimate a gravity model of workers remittances. They find remittance flows to increase for countries with larger income and the flows to be lower as distance between countries increases. But per-capita remittance flows tends to be higher for smaller countries. They also find colonial ties and trade linkages to be important in explaining remittance flows.

¹⁰such as hillside farming and deforestation

 $^{^{11}\}mathrm{Remittance}$ flows did not respond to investment opportunities in the home country

This study, however, in addition to covering only a small number of countries and a short and more recent period compared to previous studies in the literature, did not investigate the causal relationship between factors affecting remittances and natural disasters. Therefore, this result can be seen as suggestive evidence of potential reallocation of future remittances to the current period. One of the main goals of this study is to fill this gap in the literature by using monthly data and carrying out a more systematic analysis.

2.3 Data and Descriptive statistics

This study relies on data from several sources; a rich detailed panel dataset on bilateral outward remittances from Italy to 81 developing countries is obtained from the Bank of Italy¹² for the period 2005 to 2015. This data is available on a monthly basis for 250 countries for the period between 2005 and 2015, from 2016 onward data were released on a quarterly basis¹³. Remittance data at such a frequency is rarely available and hence one of the first contribution of this study is the use of such a detailed data in studying the relationship between natural disasters and remittances.

Following the literature on disasters, the study uses disaster data from the EM-DAT CRED database compiled by the University Catholique de Louvain¹⁴. The database provides information on the occurrence of disasters and their effects on people and properties as far back as 1900¹⁵.¹⁶ The paper focuses on a large set of disasters such as flooding, droughts, extreme temperature, wildfire, landslides, storms, earth quakes, volcanic activity and mass movements (dry). We further group this disasters to investigate if a heterogeneous response of remittances exist depending on the type and nature of the disaster. Additional demographic and macroeconomic data is obtained from the Italian Statistical Institute (ISTAT), the world bank and the International Financial Statistics database of the IMF. Table [2.2] below provides a list of the variables, their definition and the source from which they are obtained. To control for other shocks that may potentially affect remittance flow, data on rainfall and temperature shocks are obtained from the Centre for Climatic Research, Department of Geography, University of Delaware¹⁷.

The sample of developing countries included in this study is restricted to countries for which data on our control variables are available to allow for comparison across different specifications. Table [2.4] provides the list of countries included in our sample. The sample is composed of 81 developing countries located in all regions of the world and at different levels of development ranging from lower income countries to upper middle income countries.

¹²https://www.bancaditalia.it/statistiche/tematiche/rapporti-estero/rimesse-immigrati/index. html?com.dotmarketing.htmlpage.language=1

¹³Therefore, for the purpose of this analyses, we restrict our study to the period for which monthly data is available.

¹⁴https://www.emdat.be/

 $^{^{15}\}mathrm{Though}$ it is noted that recent data are more reliable due to better data recordings.

¹⁶The inclusion of a disaster depends on whether the event meets at least one of several criterion's; the number of people killed is at least 10, at least a 100 or more people were either displaced, injured or made homeless by the disaster, significant damages to property worth 0.5 percent of GDP were incurred, a state of emergency was declared or an international appeal for assistance was made.

¹⁷World bank climate change knowledge portal. https://climateknowledgeportal.worldbank.org/download-data

Descriptive Statistics

Disasters

Figure [2.1] shows the monthly frequency of disasters across geographic regions for the period between 2005 and 2015. We observe that South Asia experience the highest mean number of disasters occurring within a single month, averaging about eight disasters and can be high as 21 disasters for a given month. However, Europe and Central Asia displays the largest variance in the degree of occurrence of disasters about 4.9 standard deviation points.

Not surprisingly, a lot of seasonal variation in the number of disasters is observed. In terms of the severity of the disasters measured by the share of the population affected and share of population dying from disasters, Sub-Saharan Africa is the most severely affected averaging about 2.6 percent of the regions population and could be as high as 40 percent of the regions population as can be seen from figure [2.2]. The drought experienced by Niger in September 2009 affected over 7 million people, that is over 50 percent of the country's population, by far the disaster affecting the largest share of a country's population in our sample. However, in terms of deaths, Latin America and the Caribbean is the most affected region. The January 2010 earth quake that struck Haiti killed over 250,000 people, about 2.3 percent of the country's population. It is by far the single disaster with the largest human cost in terms of number of lives lost for a single disaster in our sample. Europe and Central Asia and the Middle east and North Africa on the other hand have one of the lowest rates in terms of human cost of disasters.

We also made attempts to group disasters according to their types and nature and investigate both the timing and magnitude of the response to each. We group disasters into three groups based on their subgroup classification in the EM-DAT cred database; we group hydrological and climatological disasters together and name them as climatic disasters and we retain the EM-DAT classification of geophysical and meteorological disasters. Hence our definition of climatic disasters are those that relate to the weather conditions which comprises of floods, droughts, wildfire and landslides. Our group of Geophysical disasters on the other hand are those brought by tectonic activity below the earths surface and is composed of earth quakes, volcanic activity and mass movements (dry). Our group of Meteorological disasters are instead related to the earth's atmosphere, they include extreme temperatures and storms. We note that our classification of disaster by type is different from that of David (2010) and Raddatz (2007)¹⁸ However, we prefer to use this classification which is more inline with the original groupings of the data source. To group disasters according to their nature, that is the length of time it takes before the full scale of the disaster is realised, we classify rapid occurring disasters such as as earth quakes, volcanic activity, mass movements (dry), storm, landslides and flooding as sudden-onset disasters. Extreme temperatures, wildfire and droughts are classified as slow-

¹⁸ David (2010) defined Climatic events to include floods, droughts, extreme temperatures and hurricanes; Geological events to include earthquakes, landslides, volcano eruptions and tidal waves and Human disasters to include famines and epidemics. Our study however does not include epidemics and other biological disasters.

onset disasters due to the time it takes before the full scale of the disaster is realised. Suddenonset disasters are relatively more difficult to predict compared to slow occurring disasters.

Descriptive statistics that distinguish between sudden-onset disasters and slow-onset disasters reveal that sudden disasters are more common compared to slow disasters as shown in figure [2.3a] and cause a higher fatality rate measured by the share of the population dying from such disasters. Nonetheless, slow disasters by its nature tend to affect a larger share of the population relative to sudden disasters, see figure [2.3b].

Remittance outflows and Immigrant stock

The monthly real remittance data from Italy is de-seasonalised using the standard X-12 tools to eliminate the seasonal and trend component from the series. Figure [2.4] shows the total amount of remittances in millions of euros sent from Italy to the rest of the world for the period between 2005 to 2015. Roumania receives the largest amount of remittances originating from Italy followed by other countries such as the Philippines, Bangladesh, Morocco, Peru, Albania etc. The graph reveals that between 2005 and 2011 the total remittance outflow from Italy has been steadily increasing with a slight decline in 2009 before reaching its peak of over 7.3 billion euros in 2011. From 2011 to the end of 2013, a steep decline in remittance outflows from Italy is observed before stabilising by 2015. Looking at the growth rate, one could clearly notice the sharp decline in annual growth of remittances around the period of the financial crises during which its growth decline from about 27% in 2007 to -2.6% by the end of 2010. However, the largest decline was observe between 2011 and 2013 from 10% to -20%. The reason for this sharp decline in remittances is not so obvious. Though the immigrant stock slightly declined in 2010, it started recovering from the beginning of 2011 and remained relatively constant with a slight increase from 2015 on-wards. Therefore a fall in the immigrant stock is unlikely to explain the decline in remittance outflows. Instead, a look at the unemployment statistics reveal a sharp increase in the unemployment rate from about 8 percent by the end of 2010 to a peak of 12.7 percent by the end of 2014, that is more than a 50 percent increase increase in unemployment. The cause of this decline in employment is likely related to the European sovereign crisis which began at the end of 2009. Several EU countries including Italy, Spain and Greece were severely affected. Therefore one may attribute the decline in remittances during this period to the adverse effects of the euro-zone crisis on incomes of immigrants. Next, looking at figure [2.5], a continuous increase in the stock of the immigrant population is observed¹⁹ except between 2010 and 2011 for which we observe a slight decline. In addition to having aggregate annual data on the stock of immigrants in Italy, we are also able to obtain the dis-aggregated data on the stock of immigrants available annually at province level. We exploit this data in the last section of our analyses to study how the concentration of immigrants at regional level affects the formal

¹⁹Note: Data from the Italian statistic only provides information of immigrants based on country of citizenship, therefore the figures reported here might underestimate the stock of the immigrant population.

remittance flows and their response to disasters. Details about how the concentration variable is constructed is explained in the subsequent sections.

Other Control variables

Table [3.1] presents a summary statistics of our key variables. It is important to mention here that some of the key control variables that we will ideally like to control for such as GDP, population and immigrant stock are mostly available on an annual basis for our sample of developing countries²⁰. Applying some interpolation techniques would have been an option, but noting the disadvantages associated with interpolating from annual to monthly, we desist from that and instead use various fixed effects and other controls available at monthly level. In particular, we are able to obtain monthly data for the host country on the unemployment rate which we use to proxy for the overall economic condition in the host country and the interest rate which is relevant for distinguishing between various motives for remitting and to understand the financial inclusion of immigrants These variables are important both in understanding the determinants of remittances and their possible effect on how remittances responds to disasters and shock in the origin country. We also control for the mean monthly exchange rate which we normalised to allow for easy comparison across countries²¹. We use the seasonally adjusted version of the data with the help of the X-12 tools in stata.

Previous studies have highlighted the vulnerability of developing countries to fluctuations in the terms of trade, rainfall and temperature. We are able to obtain monthly data for this variables and we control for these in our analyses. Since we are using monthly data which have a high degree of seasonality, we apply the Hodrick-prescott filter to separate the cyclical and trend components of the terms of trade.²².

On average, the number of immigrants from each country residing in Italy is about 39,000, the average monthly remittances sent from Italy to each recipient country is about 350,000 euros. On average about 13 percent of our sample experience at least one disaster during the period under consideration with the number of disasters ranging from 0 to 6 disasters in a given month. The immigrant share as a percentage of the origin country's population is on average about 0.4 percent with Immigrants from Moldova, Albania and Roumania having the largest share of immigrants relative to its population living in Italy. ²³

 $^{^{20}}$ Economic variables in the country of origin are not included due to difficulty in obtaining the relevant control variables for all periods and for all countries. However, we believe the inclusion of country fixed effect and time fixed effects in our regressions captures the effect of these variables and hence our estimates are not affected by excluding them. Although, we acknowledge that this prevents us from being able to ascertain the effect of the relevant economic variables on the on the flow of remittances.

 $^{^{21}}$ I use the real exchange rate which I further normalised relative to its value in 2010 - sort of now serving as an index. This allows for easier interpretation of the variable overcoming the issues associated with using different units of measurement.

 $^{^{22}}$ SeeBettin et al. (2015)

 $^{^{23}}$ Indeed, it would have been interesting to include the share of immigrants from a given country residing in Italy for our analyses. However, this data is not readily available as many of the countries considered in this study do not keep a track of its population residing in other countries. The closest we could get is the stock of immigrants residing in Italy as a share of the total stock of immigrants residing in the (Organisation for Economic

	Mean	SD	Min	Max
Population in millions	31.95621	45.45525	.463032	258.3833
Immigrants in thousands	38.97411	117.976	.044	1151.395
Remittances (real, 100,000 euros)	3.593648	9.555714	0	76.0714
Disaster	.112514	.3160126	0	1
Number of disasters	.1750842	.496008	0	6
Total Deaths	33.79714	2223.216	0	222570
Total Affected (Millions)	.0477618	.5233961	0	27.0006
Total Damages (Millions USD)	17.99312	441.3674	0	40000
Rainfall - (MM)	102.3728	108.1626	0	1136.15
Temperature - (Celsius)	21.20757	8.855076	-29.643	35.0319
Terms of trade trend	93.92836	13.95474	33.83324	130.3105
Terms of trade cycle	-3.75e-16	13.17212	-53.54631	83.94935
Observations	10692			

Table 2.1: Summary Statistics

2.4 Econometric specification

We exploit the exogenous nature of disasters to conduct an event study analysis. This allows us to understand the dynamics of remittances around the time when a disasters strikes in the origin country. Similar to Dobkin et al. (2018), we adopt a non-parametric event study. One of the main advantages of this approach is that it allows us to visually and flexibly observe the pattern of remittance flow relative to the time when a disaster occurs. Noting that many countries experience multiple disasters in close succession, we follow the recommended approach by Sandler and Sandler (2013) by "allowing multiple time event dummies to be turned on at once" so as to produce unbiased estimates (See Dube et al. (2010)). Sandler and Sandler (2013) showed that other methods such as ignoring subsequent events and duplicating observations yields biased estimates whilst allowing multiple time event dummies to be turned on at once yields a more nuanced and persuasive graphical analysis.

The generalised standard event study design for multiple events with an infinite effect window can be specified as follows:

$$Y_{j,t} = \lambda_j + \tau_t + \sum_{k=-\infty}^{\infty} \beta_k D_{j,t-k} + \delta_i X_{j,t} + \varepsilon_{j,t}$$
(2.1)

Where $D_{j,t}$ is an event indicator that takes the value 1 in the month-year in which a disaster occurs in country j and zero otherwise. τ_t are the calendar time fixed effects and λ_j are the country fixed effects. $X_{j,t}$ are a set of potential factors that may also affect remittance flows. Our main variables of interest here are the coefficients β_k which are indicators for time relative

Co-operation and Development) OECD, a group of high income countries whose high per-capita income makes migrants in these countries more likely to remit higher amounts. This information is also available for the entire period of our analyses for all countries. As such, we use only information on the stock of immigrants living in Italy.

to the strike of a disaster. They estimate the dynamic treatment effect k periods after a disaster occurs $(k \ge 0)$ or k periods before the disaster occurred $(k \le 0)$. In principle, for completely exogenous events, $\beta_k=0$ if $(k \le 0)$. That is, the pre-event dummies will be insignificant and if the events have any effect on the outcome variable, then the post event dummies will flexibly characterise this effect.

However, in practice it is impossible to estimate the effect window for an infinite number of periods. Therefore, we restrict our effect window to a finite number of leads and lags. We restrict the event window to \overline{k} periods after the event and \underline{k} periods before the event. The generalised event study design can hence be re-written as:

$$Y_{j,t} = \lambda_j + \tau_t + \sum_{k=-\underline{k}}^{\overline{k}} \beta_k D_{j,t-k} + \delta X_{j,t} + \varepsilon_{j,t}$$
(2.2)

Since we are restricting our effect window, this requires us to make some assumptions about the effect of the event outside the effect window. Depending on the assumption we make about events occurring outside our sample period on our estimation period and the effect of the events occurring within our sample outside the estimation period, the β_k dummies will carry different interpretations. Two possible alternatives emerge in the literature though usually not explicitly stated. One alternative is to assume the effect diminishes to zero outside the effect window. Another possibility is to assume that the effect is constant both before and after the chosen effect window. In each of our models to be estimated, we explicitly state our assumption concerning the effect of the event outside the effect window. We estimate the model above using fixed effect estimation methods. However, we note that there is a possible serial correlation in remittances at the country level and that the treatment variable (the occurrence of disasters) may be constant within each country. This may possibly bias our standard errors downwards. We therefore cluster our standard errors at the country level.

2.4.1 Baseline specification

We first estimate a simple event study analysis model only controlling for country and time fixed effects as shown below;

$$Y_{j,t} = \lambda_j + \tau_t + \sum_{k=-\underline{k}}^{\overline{k}} \beta_k D_{j,t-k} + \varepsilon_{j,t}$$
(2.3)

Where Y refers to the log of real remittance flows from Italy to immigrants country of origin j at time t. Our key dependent variable, disaster is a set of dummies that flexibly documents the dynamics of remittance flows in response to a disaster ranging from 12 months before the disaster strike to 12 months after the disaster occurred. The β_k coefficients are interpreted as semi-elasticity's of remittances with respect to a disaster. We estimate this model using all three alternative specifications mentioned earlier. That is, first with the assumption that the effect diminishes to zero outside our selected window and ignoring events occurring before and after our estimation window. Secondly, we sequentially drop this two assumptions by instead assuming that the effect is constant outside the chosen effect window and also control for disasters that occurred 12 months before and after the period for which monthly data on remittances is available. Finally, we estimate the more parsimonious specification that aggregates our leads and lags to two 6 months dummies.

2.4.2 Controlling for past and future disasters

A potential source of bias that could arise with our basic specification is if "there are location specific trends and the slopes of these trends are correlated with the event-time dummies". Aside from creating pre-trends, the results could be bias if other events with some dynamics occur outside the event window but are not observed due to data limitation (Sandler and Sandler (2014)). In our second specification [2.4], inline with the proposition by Sun and Abraham (2020), Schmidheiny and Siegloch (2020), our disaster variable is constructed to include events that occurred outside the estimation window both before and after the periods for which data on our independent variable is available.

We follow the recommendation that the event window be observed for a longer period relative to the dependent variable. According to Schmidheiny and Siegloch (2020), assuming that the dependent variable is observe for $[\underline{t}, \overline{t}]$ and the chosen estimation window is $[\underline{k}, \overline{k}]$, the event window should be observed for at least $\underline{t} - \overline{k}$ and $\overline{t} + |\underline{k}|$. This is because events that happen before \underline{t} can affect both past and current outcomes like any other events occurring between \underline{t} and \overline{t} . Similarly, it is important to control for events that happen after \overline{t} in order to test for pre-trends.

In this part of our analysis and in the subsequent sections, the study period t corresponds to [01/2005, 12/2015] and we used an effect window k of 12 months, i.e [-12,12] and data for our event window is restricted to [01/2004, 12/2016] thus allowing our dependent variable to truly capture the dynamic effect ²⁴. We maintain our earlier assumption that the effect of the event diminishes to zero outside the effect window and only dropping the assumption that events occurring outside our sample period have no effect on our estimated coefficients. We re-estimate model [2.2] and repeat the analyses above with this alternative version of our key independent variable.

 $^{^{24}}$ For instance, our analysis captures event occurring earlier than the period for which data on our dependent variable is available. eg an event occurring in November 2004 is captured by the second lag of the dependent variable

2.4.3 Binned end points with controls for past and future disasters

Next, in addition to allowing for our disaster measure to account for both past and future disasters, we also relax the assumption that the estimated effect outside the effect window diminishes to zero. Instead, we now allow for the effect of the disaster on remittances to extend beyond our effect window.

We specify the following model [2.4]

$$Y_{j,t} = \lambda_j + \tau_t + \sum_{k=-\underline{k}, k \neq -2}^{\overline{k}} \beta_k d^k_{j,t-k} + \delta X_{j,t} + \varepsilon_{j,t}$$
(2.4)

Where $d_{j,t-k}^k$ are the binned treatment indicators, such that the end-points take into account all observable events outside our effect window, i.e both past and future disasters. This binned end points are generated as follows:

$$d_{j,t-k}^{k} = \begin{cases} \sum_{k=-\infty}^{\underline{k}} & \text{if } \underline{k} = \underline{k} \\ & & \\ \sum_{k=\overline{k}}^{\infty} & \text{if } \underline{k} = \overline{k} \end{cases}$$
(2.5)

Estimating such a model "under a linearity and additive assumption yields unbiased estimates", Schmidheiny and Siegloch (2020). The variable $d_{j,t-k}^k$ is a disaster indicator equals to 1 if for a given month t, a country j experienced a disaster k months ago. However, since it is not possible to observe an infinite number of past and future events, we restrict the event outside our effect window to 12 months before and after. We believe this is sufficient to capture any possible dynamics that may be generated by the occurrence of disasters within the year.

This means we allow for the response of our dependent variable to extend outside our chosen effect window and assume that the effect does not diminish to zero but rather remains constant. We therefore bin the end observations as depicted in equation $[2.5]^{25}$. This allows us to capture all known past and future events. This is a more realistic assumption compared to the case were the effect is assumed to shrink to zero. Due to the inclusion of country fixed effects, the parameters β_k are identified only up to a constant. Therefore, to ensure that identification is achieved, we normalise our parameter estimates by expressing the parameter β_k relative to a reference period $\beta_{-2} = 0$. That is, we drop the disaster indicator $d_{j,t-2}$ (see Schmidheiny and Siegloch (2020)). This also allows for the model to be econometrically identified by separating the dynamic effects from the secular time trends even in the absence of never treated units (Schmidheiny and Siegloch (2020)). Now our parameter estimates are interpreted relative to

²⁵Binning here refers to the process of specifying the end points of the effect window to capture all events occurring before and after \underline{t} and \overline{t} respectively.

the period before the disaster strikes. In particular, the coefficient β_k estimate the outcome of a given period k relative to the omitted category β_{-k} . Insignificant coefficients of our parameter estimates in the pre-event period can be viewed as evidence that disasters are exogenous events. Our post disaster estimates characterise the response of remittances relative to the reference period. Our Standard errors are all clustered at the country level.

2.4.4 Parsimonious specification

Finally, we estimate a more parsimonious specification as in [2.6] below by collapsing the pre and post disaster parameters into coefficients of six month each, i.e. six month leads and lags instead of monthly leads and lags.

$$Y_{j,t} = \lambda_j + \tau_t + \sum_{l=-l}^{\bar{l}} \beta_l d^l_{j,t-l} + \delta X_{j,t} + \varepsilon_{j,t}$$
(2.6)

Where l refers to a lead or lag of six month interval such that l=1,2. When combining leads and lags, we do not combine the disaster indicator for the period in which the disaster occurred to maintain symmetry and also because the effect in period t is unlikely to be the same as in other periods. This parsimonious specification reduces the number of parameters to be estimated and hence allows us to add more control variables without loosing much degree of freedom. Essentially our collapsed six month leads and lags estimate the average monthly response over the six month interval.

2.5 Results

Baseline results

The results from estimating our basic specification reveals that monthly remittance flows responds positively to the occurrence of disasters. Our findings are in line with previous findings by David (2010), Balli and Rana (2015) and Bettin et al. (2018). In particular, we estimate that remittance per-capita increase by about 1.5 percent on impact and peaks at about 2.7 percent after 4 months following the disaster and averages about 1.9 percent 12 months after the disaster. This increase though marginally small is statistically significant at the 5 percent level from the second month after the disaster. Experimenting the vulnerability of our baseline estimates to a given choice of the lead and lags, we re-estimate our baseline model by varying the number of leads and lags as can be seen from table [2.5]. In column [1], we include 3 leads and 12 lags of the disaster dummy and in column [2] we extend the number of leads controlled for to 6 and the number of lags to 18. In column [3], we restrict the number of leads to 3 and extend the number of lags to 24 and in column [4] we extend the number of leads to 12 months prior and 24 months after the disaster. Our estimated response of remittances per-capita to the occurrence of a disaster is robust to controlling for different number of leads and lags albeit with a marginal drop in the magnitudes of the estimated coefficients as the number of parameter to be estimated increases. We find that on average remittances increase by about 2 percent monthly relative to the excluded periods prior to the disaster. This increase is persistent over the next 12 months after which the response is statistically insignificant. As can be seen from the graph [2.6b] and [2.7b] in which our leads extend further back beyond the three months, there seems to be an increasing trend in remittance flows despite de-seasonalising the data and controlling for month-year time fixed effects. However, a t-test for all the leads fails to reject the hypothesis that the leads are jointly equal to zero but strongly rejects the hypothesis that the lags are jointly equal to zero even at the 1 percent significance level.

Adopting the specification with 3 leads and 12 lags as our preferred baseline specification, controlling for additional variables that are available at monthly interval does not affect the results. In particular, we control for the cyclical and trend components of the terms of trade, mean monthly rainfall and temperature and mean monthly exchange rate of the origin countries. For the host country, we control for a proxy for economic activity using the monthly unemployment rate. Our estimated coefficient for the response of remittances on impact is robust to this additional controls, the estimated response is about 1.6 percent on impact though not statistically significant but from the month after the disaster this effect is statistically significant with a peak at the end of the first quarter after the disaster occurred. Column [1], [2] and [3] of table [2.6] presents the estimates²⁶.

Our result on the response of remittances to disasters is contrary to previous findings by Bettin et al. (2014) which did not find any effect of disasters on remittances. However, it is important to note that Bettin et al. (2014) used provincial level data which is likely to be less responsive due to its small volume and the small size of the immigrant population residing in each province. Furthermore, the use of annual data mask the potential heterogeneity we investigate in this paper. Besides, we also argue that our event study approach alongside the use of monthly data allows for better identification of the effect of disasters on remittances.

Controlling for past and future disasters

To eliminate the trends we observe in figures [2.6] and [2.7] above, we adapt an alternative specification in line with recent advances in the literature on event studies for multiple events. The trends we observe in these figures may suggest that other unrelated trends maybe driving

 $^{^{26}}$ As a way of trying to account for seasonality of disasters and or of remittances, we also estimated the model using quarter by country fixed effects separately and also using both the month-year fixed effects and quartercountry fixed effects. In both specifications, the pre-trends observe earlier still persist but remain statistically insignificant and now all our post-disaster coefficients becomes individually insignificant though jointly are marginally significant for the first specification. However, it is important to highlight that such strategy is computationally demanding, requiring an additional 3500 parameters to be estimated.

the results or rather events are not completely exogenous but are somehow anticipated. Aside from creating pre-trends, the results could also be bias if other events with some dynamics occur outside the event window but are not observed due to data limitation. One way to mitigate this will be to collect data on disasters outside our sample period and control for such events in the analysis. In our case, we have a panel data on disasters over a relatively longer period from 1990 to 2019. We avoid this potential problem by extending our analysis to include other events occurring outside our sample window. Our new disaster measure now includes disasters occurring earlier than 2005 and beyond 2015 to allow us capture any dynamics that maybe attributed to disasters.

We re-estimate model [2.3] with our alternative disaster measure and repeat the analyses conducted above. The findings from this approach are similar to our earlier findings both in magnitude and significance. However, now the trends in the pre-disaster periods are eliminated allowing for a clear breakthrough in the pattern of response to be observed around the time of the event. Table [2.7] presents the full results for these analyses and figures [2.8] and [2.9] presents the plots of the dynamic response in the baseline specification with different number of leads and lags. We now clearly see a jump in remittances around the time the disaster strikes and the estimated response of remittances on impact is now about 1.8 percent relative to the periods outside the effect window but is still not statistically significant. The response is only significant from the second month onward with a peak of 2.4 percent in the fourth month and a monthly average of a little over 2 percent.

These findings are robust to controlling for other shocks such as the trend and cyclical fluctuation in the monthly terms of trade, monthly rainfall and temperature as can be seen from table [2.8]. Similarly, the results are also unaltered by controlling for other economic conditions such as the proxy for the economic condition in the host country and the real exchange rate. The magnitude of the estimates slightly increases and remain statistically significant. Controlling jointly for other shocks and economic conditions does not alter either the magnitude of the estimated coefficients or its significance. The results for our control variables are similar as those presented earlier.

Controlling for past and future disasters and binning the end points

Relaxing the assumption that the effect of disasters diminishes to zero outside the chosen effect window, we estimate model [2.4] and present the result in table [2.9]. Unlike our previous results, these results are expressed relative to two months before the disaster occurred, the dummy $\beta_{k=-2}$ is set equal to zero and hence serve as the reference point²⁷. Our findings reveal a clear increase in remittances at the time the disaster strike and in the following months as can

 $^{^{27}}$ Most studies set k=-1 or k=0 as reference points, however in our case since some of this disasters might have been predicted due to their seasonality or through weather forecast information, we arbitrarily choose two months before the event.

be seen on figure [2.10a]. We estimate a statistically significant increase of about 1.2 percent in remittances on impact relative to two months before the disaster occurred. This increase to a peak of about 1.6 percent in the fourth month after the disaster strike relative to mean remittances two months before the event occurred, all estimates being statistically significant at the 5 percent significance level. Beyond the fourth month, the increase though positive is not always statistically significant.

The estimates on our binned coefficients are not statistically different from zero. This means we cannot reject the hypothesis that the response of remittances diminishes to zero in the long run, that is beyond the one year event window. This however is not surprising noting the low magnitude of response we observe within the 12 month window.

Even with the binned specification, our results are robust to controlling for either other shocks such as the trend and cyclical fluctuation in the terms of trade, rainfall and temperature. Likewise to controlling for other economic conditions as can be seen from column [2] to [4] of table [2.9].

2.5.1 Robustness Checks

In addition to the various alternative specifications used above, we test further for the robustness of our main results reported above to a variety of alternative disaster measures. First, one may expect that the response of remittances is not independent of the number of disasters that occur within a month. We test for this by replacing the disaster dummy with the number of disasters occurring during a month. Our findings are inline with our earlier findings, our coefficient estimates remains statistically significant and the magnitudes are quite similar.

Second, we restrict our attention to only disasters of relatively larger magnitudes. We do this by restricting our attention first to disasters above the 25th percentile of the distribution of the share of the population affected and then later to those above the 50th percentile of the share of the population affected. Our findings are inline with previous findings with the magnitudes of the coefficient being much larger for disasters above the 50th percentile. This confirms the hypothesis that the response of remittances is larger for disasters with a larger magnitude which is quite reassuring. Table [2.10] presents the results. Column [1] presents the estimates from our preferred basic specification using the disaster dummy as the measure of disaster, column [2] presents the results from using the frequency of disaster while column [3] and [4] presents the results from using the share of population affected.

Parsimonious specification

In this section, we estimate a parsimonious version of our dynamic specification by collapsing the pre and post disaster parameters to be estimated. We do this by estimating the average monthly response over a six or twelve month period. That is, now the collapsed dummies takes on the value one for six period intervals.

Table [2.11] presents the results from estimating model [2.6] where we allow the six month interval dummy to capture the six or twelve month average monthly response of remittances to the occurrence of a disaster. In column [1], we presents the results from collapsing the 12 month pre and post disaster variables into one single dummy. The estimated pre-disaster variable though positive is statistically insignificant, likewise the estimated response on impact. On the other hand the aggregated post disaster coefficient over a 12 month horizon is 1.8 percent and is statistically significant at the 10 percent significance level. However, once we cluster the standard errors at the country level, the estimates becomes statistically insignificant. Our findings for the response of remittance to disaster are similar when we use six months leads and lags. This result suggests that for the case of remittance outflows from Italy, its response to natural disaster is marginal and is only observed with monthly data when measured at monthly intervals. Using aggregate data and conducting the analyses at aggregate level say annually mask this marginal response of remittances to disasters as can be seen in Bettin et al. (2015). Therefore, this study can be seen as potentially helping to reconcile the disparate findings on the remittance-disaster nexus.

2.6 Additional analysis

In this section, we use our efficient specification [2.6] to explore the implication of our main results further. First, we investigate whether there is any heterogeneity in response to disasters based on the size of the immigrant stock and the level of development of the immigrants origin country. Second, we also examine if immigrants response to disasters in stable or good macroeconomic conditions in the host country differs from their response when the economic conditions in the host country are not favourable. That is, we focus on how the recent economic events such as the global financial crises and the euro-zone crises have affected the response of remittances to shocks occurring in the immigrants country of origin. Thirdly, we investigate if there exist a heterogeneous response of remittances based on the type of the disaster. Finally, we categorise disasters based on their nature of occurrence, that is either slow occurring or sudden onset disasters to investigate both the timing and magnitude of response to each type.

Heterogeneity by size of immigrant stock

In Column [5] of table [2.8], we present the estimates from restricting the sample to only a sub-set of countries with a relatively larger stock of immigrants. As expected, our coefficient estimates are now larger, increasing by about 2.9 percent on impact and is statistically significant. The estimated response peaks after four months with an increase of about 3.6 percent. This can be seen as suggestive evidence on the important role that the stock of the immigrant play in the magnitude of the remittance flows in line with earlier findings by Bettin et al. (2014) and Mohapatra et al. (2012) among others²⁸.

Heterogeneity in response by origin country's Level of Development

We split our full sample into different sub-samples based on the origin country's level of development; that is, lower income, lower middle income and upper middle income countries. Using the efficient specification model [2.6], we estimate the response of remittances to disasters for each sub-sample.

We find that the positive and significant response of remittances we found earlier are mostly driven by the large response to disasters occurring in upper middle income countries²⁹. Table [2.12] presents the results. Though the estimated sign of the post disaster coefficients are all positive, they are only significant for the group of upper middle income countries. The estimated response on impact is about 1.4 percent and peaks at about 1.5 percent in the fourth month. This means that our estimates are driven by the flows to upper middle income countries.

Heterogeneity in response by economic phase in host country

We conduct heterogeneity based on the period during which disaster occurred. We divide the time period into three; the phase prior to the global financial crises 2005-2008, the phase of the global financial crises and euro-zone crises 2009-2012, and the recovery phase 2012-2015. we find that the results are mainly driven by response to events that occurred prior to the financial crises. The respond of subsequent events were not statistically different form zero. Table [2.13] presents this results. Our findings estimate that remittances increased on impact by about 2 percent in response to disasters that occurred between 2005 and 2008 with a peak of about 4 percent eight months after the disaster. This estimates are statistically significant up to 10 months after the disaster. This findings are inline with some of the earlier results on this topic that mostly focused on periods prior to the financial crises³⁰. However, our findings reveal that around the period of the financial crises, there was no significant response of remittances to disasters that occurred during that period. This was however complemented by a relatively larger response to disasters occurring in the aftermath of the crises. For the sub-period 2012 to 2015, remittances responded on impact by about 4.2 percent. This response was statistically significant though the response was only short-lived.

 $^{^{28}}$ We do not control for the stock of immigrants explicitly in our model because this information is available only at an annual interval and interpolating this to monthly will not add much to the analysis.

 $^{^{29}}$ However, we note that this is likely related to the relatively larger stock of the immigrants originating from upper middle income countries. ³⁰See Mohapatra et al. (2012) and David (2010) among others

Heterogeneity in response by type of disaster

We also investigate the heterogeneity of response based on the type of disaster. Specifically, we aggregate disasters into three main types namely; Climatic, Meteorological and Geophysical. We used the binned specification to estimate how remittances responds to the different types of disasters by expressing this response relative to two months prior to the occurrence of the disaster. Figures [2.11a], [2.11b] and [2.11c] plots the graph of this dynamic response and table [2.14] presents the estimates. We observe that remittances are higher in the post disaster period relative to the period prior to the occurrence of a disaster for climatic and meteorological disaster but not for geophysical disasters. This seems quite intuitive since earthquakes and tsunami's are likely to be very localised with more severe consequences especially on the existing capital stock, thereby disrupting channels through which remittances are sent such as infrastructures and telecommunication facilities. We estimate a relatively larger response of remittances to meteorological disasters compared to climatic disasters, however, the response to the former is only statistically significant in the second period of the disaster. While the estimated effect for climatic disasters is significant from the month month after the disaster to the fourth month as can be seen from table [2.14]. This findings are a bit similar to earlier findings by David (2010) in his extended fixed effect panel specification that controls for a deterministic trend. David find a significant response of remittance only to climatic disasters on impact³¹.

Heterogeneity in response by nature of disaster

Furthermore we classified disasters into two main types, namely sudden onset disasters and slow onset disasters based on the degree to which this events can be predicted. We find that the response to sudden events, though smaller in magnitude is much more swift. The estimated increase on impact relative to two months before the disaster occurred is about 1.3 percent and is statistically significant at the 5 percent level. This effect remains significant for the four months following the disaster and increases up to about 1.5 percent in the fourth month. Figure [2.12b] plots this dynamic response and column [5] of table [2.14] presents the coefficient estimates.

On the other hand, the response to slow disasters is only significant from the second month after the disaster occurred. The estimated increase in the second month is about 2.6 percent and it remains statistically significant and continue to increase in each subsequent month to a peak of about 4 percent in the 8th month after the disaster occurred. This is not surprising since the effect of slow disasters such as droughts and flooding that are more usually widespread, damage crops and kill livestock's on a larger scale. However, its full effect may not be immediately realised but rather its severity is likely to be more pronounced overtime, thus requiring larger

 $^{^{31}}$ Though our composition of the various groups of disasters differs as mentioned earlier as well as the how the disaster measure is constructed.

support for a sustained period to recover from its effects fully. Hence we expect a much larger response to such disasters. Figure [2.12a] plots this dynamic response and column [4] of table [2.14] presents the coefficient estimates.

2.7 Immigrants concentration and location

Another important contribution of this study aside from using monthly data, robustly documenting the dynamic monthly response of remittances in the aftermath of a disaster, and investigating the main channels driving the observed response, is the analysis of the role of "networks"³². That is, how the distribution and location of migrants in the destination country influences the flow of remittances and its response to shocks occurring in the origin country. Despite an overwhelming evidence on how the concentration of immigrants and their place of residence affects their level of economic integration, previous studies analysing the determinant of remittances and its response to natural disasters have paid little attention to it. This study is one of the first that attempts to explicitly model how the spatial distribution of migrants might affect the size of remittances originating from the host country as well as its response to the occurrence of shocks in the origin country. This is important because both the distribution and location of the migrant population might have a heterogeneous effect on both the earnings of immigrants and their response ability to emergency situations³³. We first asses if the distribution have any effect in determining the flow of remittances and then further investigate if it plays any role in determining post disaster remittance flows.

The main objective of analysing the potential role of the location and clustering of migrants are; firstly, to investigate if the clustering of migrants may affect their response to the occurrence of a disaster in the home country³⁴. Secondly, to investigate to what extent does the north south divide drive the response of remittances to natural disasters. The location serving as a proxy for the economic potential or response ability of immigrants. Assessing the economic relevance of these issues are also relevant to understanding of the factors affecting migrant integration and their contribution to their countries of origin.

2.7.1 Network effects: Immigrant concentration

We define migrants concentration as the degree to which a sending country's emigrant population are dispersed across different locations in the host country³⁵. In this study we focus on the relative distribution of immigrants across different Italian provinces³⁶. The concentration

 $^{^{32}}$ Networks is measured here by the concentration of immigrants in a province.

 $^{^{33}}$ This is even more relevant for the case of Italy where the economic disparity between the North and the South is overwhelmingly evident.

³⁴Migrants response being proxied here by formal remittance flows.

 $^{^{35}}$ See Jayet et al. (2010b) who studied the location of immigrants in Italy with an attempt to disentangle between networks and Local Effects

 $^{^{36}}$ Data of immigrant stock is available also at the commune level but this figures are quite small and often at times zero. Besides, the formation of networks are likely to extend to relatively broader geographical areas,

of immigrants needless to mention is also known to be associated with some negative consequences. It has been shown that clustering of immigrants may affect immigrants economic integration in the host country such as delaying the rate of acquiring of the host country's language, discouraging investment in skills relevant to the host country thereby affecting their nominal earning and retarding their upward economic mobility (See Borjas among others).

Nonetheless, we posit that high concentration levels allows for the emergence of local money sending institutions that facilitate the flow of remittances³⁷. Importantly, we hypothesise that it allows for easy organisation into groups that may potentially facilitate the collection and transfer of collective remittances in emergency situations such as the occurrence of a disaster³⁸. This is in addition to helping spread the news about the event and its devastating consequences on the livelihoods of those left behind especially in an environment where there is imperfect information. Notwithstanding, there may be negative externalities associated with the concentration of migrants in the same locality as has been highlighted in the literature on migrant integration. For instance, a higher concentration is likely to result in the concentration of immigrants economic opportunities to few sectors and may therefore lead to a higher vulnerability to shocks that are region specific. Thus resulting in lower earnings and limiting their ability to respond to shocks in the origin country.

We propose the following measures of geographic concentration;

1. A Simple measure of migrant concentration will be to just compute the per-capita migrant in each location by simply dividing total migrant population from each country in each province by the total land area of the province.

$$MC = \frac{M_{j,p,t}}{A_p} \tag{2.7}$$

Where M refers to the stock of the immigrant population originating from country j residing in province p at time t and A refers to the land area of province p. However, such a measure does not account for the distribution of the native population as well as the economic attractiveness of the province.

2. A better measure for the geographic concentration of immigrants is the one which also takes into account the geographic distribution of the native population. We propose a modified version of the geographic concentration measure propose in the literature. We define our geographic concentration of migrants as follows;

$$GC = \sum_{i=1}^{N} |M_{j,p,t} - P_{d,t}|$$
(2.8)

Where M refers to the share of the immigrant population from country j residing in province

economic activities are also highly correlated at more aggregate levels such as provinces in our case. Therefore, we choose to focus at relatively higher levels of aggregation.

 $^{^{37}}$ However, we do not loose sight of the fact that this institutions could either be formal or informal or both. 38 Whether we observe this depends on the channel use in sending such remittances.

p at time t. P is defined as the share of the native Italian population in province p at time t and i=1...N refers to the number of Italian provinces. However, this index have been noted to underestimate the geographic concentration of foreigners where the level of aggregation (provinces) are large. In fact in an event that all the immigrants from a specific country are concentrated in the province with the smallest population of natives, the index reaches its maximum.

$$GC^{max} = \sum_{i \neq min} P_{p,t} + 1 - P_{min} = 1 + 1 - 2(1 - P_{min})$$
(2.9)

$$GC^{max} = 2(1 - P_{min})$$
 (2.10)

Where P_{min} is the natives share in the province with the smallest number of Italians. To circumvent this, a normalised version of this index has been proposed to correct for the bias. The Adjusted geographic concentration index:

$$AGC = GC/GC^{max} \tag{2.11}$$

which scales the GC by its possible maximum measures the difference between how immigrants are geographically distributed in the host country relative to the geographic distribution of the native population. The index ranges between 0 (no concentration) and 1 (maximum concentration).

Since we have only annual data on immigrant stock, we construct the various indices for each year and classify countries into three groups namely; low concentration for countries whose distribution is below the 25th percentile, medium concentration for those within the 25th and 75th percentile and high concentration for those above the 75th percentile of the distribution. We create dummies for each category and use it as a control variable in our regression alongside with the log of the annual stock of immigrants for each country. Note that this approach allows us to exploit variation within a migrant group overtime and between groups overtime³⁹.

2.7.2 Italy's North-South divide

In Italy, the economic situations are very different between the north and the south⁴⁰. We leverage this natural north-south divide to investigate its effect on the size of remittances sent by immigrants living in each of these two regions. We use the NUTS (Nomenclature of Territorial Units for Statistics) codes of Italy and group the five main regions of Italy into North and South. The three NUTS1 regions of Northwest, Northeast, and Central Italy are grouped and classified as Northern Italy due to their relatively better economic conditions and

³⁹In this case since we have annual data, we can only exploit variation between different years and not months. ⁴⁰Many theories have been advanced for this "dualism" of the Italian Economy and its consequent (see Rungi and Biancalani (2019), among others

the remaining two NUTS1 region of South Italy and its Insular Islands of Sicily and Sardinia as Southern Italy.

We compute the share of each origin country's immigrant population living in the north of Italy for each period by simply dividing the total number of an immigrant groups population living in the north by its total stock in Italy. However, the main setback with this approach is that the stock of immigrants is only available at an annual level whilst our analysis is being conducted at monthly level. Nonetheless, we are still able to exploit both the variation for a give country across different years and between countries by year.

2.7.3 Results

Table [2.15] presents the results from estimating the effect of the distribution and location patterns of migrants within the host country on remittance flows. Our baseline results presented in column [1] of table [2.15] does suggest that immigrant groups with moderate concentration send high amounts of remittances relative to immigrant groups with low concentration. We estimate that immigrant groups with a medium concentration index remit about 17 percent higher relative to those with lower concentration, this estimate is statistically significant at the 10 percent level. In column [2] when we control for only the share of the immigrants residing in the north, the relatively more economically advanced part of the country, we find a 1 percent increase in the share of a country's population residing in the north leads to about 2.6 percent increase in the amount remitted. This is inline with our expectation. In column [3], when we control for both factors jointly, our findings indicate a robust effect albeit with a slightly lower magnitude.

To understand how both factors may jointly affect remittance flows, we generate an indicator for immigrant groups whose share of the immigrant population living in the north is greater than the mean share for the entire immigrant sample living in the north and interact it with the concentration index computed earlier⁴¹. Column [4] of Table [2.15] reports the estimates. This is inline with the hypothesis that a higher concentration of immigrants may help maintain strong social ties with the origin country and also facilitate the emergence of money sending institutions thus encouraging the flow of more remittances to the immigrants origin country. Likewise it also supports the theory that the size of remittances are dependent on the economic ability of immigrants.

We find that immigrant groups with a very high concentration index and a large share of its nationals residing in the north tend to remit about 9.5 percent less than those located in the south, these estimates are statistically significant at the 10 percent level. The reason for this is not very obvious. Drawing insights from previous literature, one of two possible mechanism may be at play; high concentration of immigrants is likely to limit the economic

 $^{^{41}}$ Recall that the concentration index is divided into three groups with 1 referring to low concentration, 2 for medium concentration and 3 for high concentration

opportunities of immigrants⁴² and hence the amount of remittances that could be sent. Another possible mechanism is through the emergence of informal money transfer channels that may divert remittances away from formal channels. However, we are unable to investigate this issue further to distinguish which of this channels is actually at play.

Controlling for other shocks such as the monthly cyclical fluctuation in the terms of trade, rainfall and temperature as well as proxies for the economic conditions in the host country and other macroeconomic characteristics neither affects the sign of our coefficients and its significance as can be seen in columns [5] to [7] in table [2.15]. This results persist both when we control for each group separately or jointly.

2.8 Determinants of post disaster remittance flows

Previous studies find that the share of newly arrive immigrants and the economic conditions in the host country are important determinants of post disaster remittance flows (see Lueth et al. (2006), Yang (2008) and Bettin et al. (2014) among others). This study extends this analysis further by interacting additional determinants of remittances with the disaster measure to understand if these factors in anyway have an effect on how monthly remittances respond to disasters.

To study the determinants of post disaster remittance flows from Italy, model [2.6] is augmented to further control for the interaction between our various control variables and our preferred disaster measure. We use the efficient specification to conserve space and for easier presentation and interpretation of the results.

$$Y_{j,t} = \lambda_j + \tau_t + \sum_{l=-\underline{l}}^{\overline{l}} \beta_l d^l_{j,t-l} + \delta X_{j,t} + \gamma X_{j,t} * d^l_{j,t-l} + \varepsilon_{j,t}$$
(2.12)

Where $X_{j,t} * d_{j,t-l}^l$ is the interaction term between our control variables and our preferred measure of disaster. We sequentially add our control variables to identify the most important factors and how the inclusion of additional variables affect our results.

To the best of our knowledge, this study is the first to study how the concentration and place of residence of immigrants in the host country might affect their response to disasters occurring in the origin country. This s in addition to the fact that this study is also the first to examine the determinants of monthly remittance flows.

⁴²see Borjas

2.8.1 Macroeconomic characteristics

To study the macroeconomic determinants of post disaster remittance flows from Italy, we use model [2.12] to further control for the interaction between the macroeconomic characteristics of the origin and destination country with our preferred disaster measure.

We control mainly for economic variables for which data is available at a monthly level without any need for interpolation to avoid the problems associated interpolating the data. We use the monthly unemployment rate as a proxy for the economic conditions of the host country and other additional variables such as monthly interest rate and the real exchange rate. I normalised the exchange rate using 2010 as the base year. We sequentially interact each of this controls with our preferred disaster measure⁴³ to gauge if the estimated response to disaster is affected by any of these factors.

2.8.2 Geographic and location factors

To study if the dispersion and place of residence within the host country have any effect on how migrants might respond to disaster and other shocks occurring in the origin country, we interact our measures of migrant dispersion and location with our measure of disaster in model [2.12] above. As we have seen from the previous section, there is a large heterogeneity between remittances originating from the north vs those originating from the south in response to disasters. We interact our measure of migrant concentration and also our variable measuring the share of the migrants in the north with our disaster measure to understand if post disaster remittance flows are influenced by either of this.

2.8.3 Results

Column 1 of Table [2.16] presents the results from interacting the location variable with the disaster measure and column 2 from interacting the Adjusted concentration index with the disaster variable. Our results reveal that the post disaster remittances flows are mainly driven by remittances originating from the south and that remittance flows from the north falls when a disaster occurs in the origin country. We estimate the former to increase by about 28 percent and the latter to decline by about 43 percent and both are statistically significant at the 5 percent level. Similarly, we find migrants with a medium concentration index remit about 5 percent less than those with low concentration. The coefficient with high concentration though negative is not significant. However, wen we control for both factors jointly, only the interaction of the share of the population in the north and the disaster dummy remans significant. These results are robust to jointly controlling for other shocks and macroeconomic characteristics

 $^{^{43}\}mathrm{That}$ is, the measure that also takes into account past and future disasters.

either separately or jointly does not change the sign and significance of our estimates albeit a marginal change in the magnitude of the estimated coefficients.

Table [2.17] shows the results from interacting the macroeconomic characteristics with the disaster variable. All two variables suggest a positive response to disaster, however none of them is statistically significant.

2.9 Conclusion

In this study we flexibly document the dynamic response of monthly remittances from Italy to the occurrence of natural disasters in the immigrants origin country. We find strong evidence that monthly remittances from Italy increases in the aftermath of a disaster occurring in the origin country. Our findings are robust to different ways of constructing our disaster variable and to various assumptions regarding the effect of disasters outside the chosen effect window and to controlling for many factors that may affect remittance outflows. Exploring the heterogeneity of the response, We find that the nature of this response is related to the level of development of the origin country, the economic phase of the host country and the nature and type of disasters being studied. We also find that to a lesser extent remittances also serve as a shock absorber to other events occurring in the origin country such as a decline in rainfall.

This study also documents the effects of the geographic concentration of migrants and their location within the host country on remittance flows as well as how it serve as a determinant to how remittances responds to disasters. We find that immigrants living in the north of Italy tend to remit more due to the better economic conditions in the north. However, our findings suggest that a higher concentration of immigrants in a province is associate with lower amount of remittances. We also find evidence that the response of remittances to disasters is strongly affected by immigrants place of residence within the host country with migrants in the south displaying a higher level of altruism with respect to disasters. Our study however do not find much evidence that the concentration of immigrants and or the general macroeconomic conditions prevailing in the host country to be significant determinants of the post disaster remittance flows.

2.10 Appendix

Table 2.2:	Variables	and	sources
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Variable	Description of variable	Variable source
REMIT	Aggregate real monthly remittance flow from Italy to country j at time t	Bank of Italy
DISASTER	Indicator of weather a country experienced a natural dis- aster	EM-DAT, CRED
No. Disaster	Total number of natural disasters experienced by country j at time t	EM-DAT, CRED
Share affected	Share of country's population affected by a disaster(s) in country j at time t	EM-DAT, CRED
Terms of trade cy- cle	computed by applying the Hodrick–Prescott filter to the Logarithm of the commodity price index at time t	IMF
Terms of trade trend	computed by applying the Hodrick–Prescott filter to the Logarithm of the commodity price index at time t	IMF
Rainfall	Mean monthly rainfall (mm) for each country	World bank cli- mate change knowl- edge portal https: //climateknowledgeportal. worldbank.org/ download-data
Temperature	Mean monthly temperature (degree celcius) for each country	World bank cli- mate change knowl- edge portal https: //climateknowledgeportal. worldbank.org/ download-data
EXCHANGE RATE	The real exchange rate of country j for one U.S dollar at time t	IMF-IFS ⁴⁴
INTEREST RATE	Domestic interest rate in host country at time t	IMF-IFS
UNEMPLOYMENT RATE	Domestic unemployment rate in host country at time t	IMF-IFS
IMMIGRANTS	Annual stock of immigrants in Italy both at national level and at regional level from country j at time t	Italian National Insti- tute of Statistics (IS- TAT)



Figure 2.1: Frequency of natural disasters

Table 2.3: Summary Statistics

	Mean	SD	Min	Max
Population in millions	31.95621	45.45525	.463032	258.3833
Immigrants in thousands	38.97411	117.976	.044	1151.395
Remittances (real, 100,000 euros)	3.593648	9.555714	0	76.0714
Disaster	.112514	.3160126	0	1
Number of disasters	.1750842	.496008	0	6
Total Deaths	33.79714	2223.216	0	222570
Total Affected (Millions)	.0477618	.5233961	0	27.0006
Total Damages (Millions USD)	17.99312	441.3674	0	40000
Rainfall - (MM)	102.3728	108.1626	0	1136.15
Temperature - (Celsius)	21.20757	8.855076	-29.643	35.0319
Terms of trade trend	93.92836	13.95474	33.83324	130.3105
Terms of trade cycle	-3.75e-16	13.17212	-53.54631	83.94935
Observations	10692			



Figure 2.2: Share of population affected by natural disasters

Figure 2.3: Frequency of Disasters and share of population affected by nature of disaster



(a) Frequency of disaster











Angola	0.041
Albania	10.173
Argentina	1.727
Armenia	0.053
Azerbaijan	0.020
Burundi	0.040
Benin	0.478
Burkina Faso	1.057
Bangladesh	18.547
Bulgaria	3.891
Bosnia and Herzegovina	0.280
Belarus	0.308
Bolivia	2.362
Brazil	10.859
Central African Republic	20.020
Cote d'Ivoire	1.931
Cameroon	1.104
Congo, Dem. Rep.	0.534
Congo, Rep.	0.121
Colombia	7.343
Cabo Verde	0.314
Costa Rica	0.186
Dominican Republic	7.694
Algeria	0.144
Ecuador	10.464
Egypt, Arab Rep.	1.375
Ethiopia	0.251
Gabon	0.040
Georgia	3.873
Ghana	1.979
Guinea	0.137
Guinea-Bissau	0.076
Guatemala	0.183
Honduras	0.588
Haiti	0.047
Indonesia	0.465
Jamaica	0.096
Jordan	0.126
Kazakhstan	0.131
Kenya	0.621

Table 2.4: List of countries and average monthly remittances received (millions of euros)

Kyrgyz Republic	0.257
Cambodia	0.037
Lebanon	0.164
Liberia	0.032
Sri Lanka	7.160
Morocco	21.668
Moldova	5.423
Madagascar	0.225
Mexico	0.445
Mali	0.631
Mongolia	0.013
Mozambique	0.035
Mauritania	0.046
Mauritius	0.215
Malawi	0.011
Malaysia	0.090
Niger	0.083
Nigeria	3.935
Nicaragua	0.180
Nepal	0.140
Peru	12.999
Philippines	41.765
Paraguay	0.473
Romania	63.888
Russian Federation	12.674
Rwanda	0.044
Senegal	18.166
Sierra Leone	0.070
El Salvador	1.352
Chad	0.045
Togo	0.530
Thailand	0.837
Tunisia	5.359
Turkey	1.472
Tanzania	0.352
Uganda	0.166
Ukraine	9.932
Venezuela, RB	0.211
Vietnam	0.132
South Africa	0.118
Zambia	0.035

Remittance PC Remittance PC Remittance PC Remittance PC 3 months before Disaster .017 .0124 .0126 .0123 2 months before Disaster .0108 .0.0146 .0.0146 .0.0146 1 months before Disaster .0.0181 .0.0140 .0.0130 .0.0130 Month of Disaster .0.0184 .0.0147 .0.0130 .0.0130 1 month after Disaster .0.020* .0.015* .0.016* .0.0105* 2 month after Disaster .0.020* .0.015* .0.016* .0.000* 3 month after Disaster .0.011* .0.000* .0.000* .0.000* 5 month after Disaster .0.011* .0.000* .0.000* .0.000* 6 month after Disaster .0.011* .0.000* .0.000* .0.000* 6 month after Disaster .0.011* .0.000* .0.000* .0.000* 7 month after Disaster .0.011* .0.000* .0.000* .0.000* 9 month after Disaster .0.013* .0.000* .0.000* .0.000*		(1)	(2)	(3)	(4)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		Remittance PC	Remittance PC	Remittance PC	Remittance PC
(.0105) (.0099) (.0105) (.0144) 1 months before Disaster (.0097) (.0088) (.0106) (.0124) 1 months before Disaster (.0097) (.0088) (.0108) (.0107) Math of Disaster (.0131) (.0108) (.0107) (.0108) (.0108) 1 month after Disaster (.0108) (.0111) (.0108) (.0108) 2 month after Disaster (.0204) (.0157) (.0097) (.0097) 2 month after Disaster (.0215) (.0109) (.0108) (.0101) (.0097) 3 month after Disaster (.0215) (.0097) (.0097) (.0107) (.0097) 4 month after Disaster (.0111) (.0097) (.0100) (.0101) (.0097) 5 month after Disaster (.0117) (.0108) (.0097) (.0100) (.0107) 6 month after Disaster (.0117) (.0087) (.0101) (.0097) 7 month after Disaster (.0121) (.0107) (.0177) (.0181) (.0097) 10 mont	3 months before Disaster	.0117	.0124	.0126	.0129
2 nonths before Disaster .0138 .0148 .0146 .0146 1 months before Disaster .0137 .0133 .0130 .0130 1 month after Disaster .0160 .0109 .0109 .0109 .0109 2 month after Disaster .0100* .0110 .0109 .00065 .00090 2 month after Disaster .0200* .0110* .00055 .00065 .00085 3 month after Disaster .0200* .0219* .0213* .0200* .0227* 4 month after Disaster .0210* .0010* .0008* .0117* 5 month after Disaster .0210* .0100* .0008* .0117* 6 month after Disaster .0010* .0008* .0110* .00029* 6 month after Disaster .0175 .0181* .0174* .0174* 7 month after Disaster .0175 .0181* .0174* .0174* 7 month after Disaster		(.0105)	(.0099)	(.0105)	(.0104)
1 1 1.0137 (.0136) (.0136) (.0137) (.0137) Month of Disaster (.0154) (.0168) (.0098) (.0098) 1 month after Disaster (.0103) (.0103) (.0103) 2 month after Disaster (.0103) (.0103) (.0103) 2 month after Disaster (.0207) (.0103) (.0103) 3 month after Disaster (.0213) (.0101) (.0097) (.0008) 4 month after Disaster (.0213) (.0101) (.0003) (.0100) 5 month after Disaster (.0113) (.0097) (.0100) (.0100) 5 month after Disaster (.0111) (.0098) (.0100) (.0107) 6 month after Disaster (.0173) (.0187) (.0123) (.0179) 7 month after Disaster (.0173) (.0184) (.0179) (.0164) (.0179) 9 month after Disaster (.0173) (.0184) (.0179) (.0184)	2 months before Disaster	.0138	.0148	.0146	.0154
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	1 months before Disaster	.0127	.0136	.0130	.0136
Month of Disaster (0.154) (0.154) (0.164) (0.103) 1 month after Disaster (0.103) (0.102) (0.009) (0.009) 2 month after Disaster (0.008) (0.0101) (0.009) (0.009) 3 month after Disaster (0.215************************************		(.0095)	(.0098)	(.0098)	(.0097)
1 nonth after Dinaster $(0.130)^{\circ}$ (0.012) (0.009) (0.009) 2 month after Dinaster $(0.103)^{\circ}$ $(0.002)^{\circ}$ $(0.008)^{\circ}$ 3 month after Dinaster $(0.103)^{\circ}$ $(0.002)^{\circ}$ $(0.002)^{\circ}$ 4 month after Dinaster $(0.116)^{\circ}$ $(0.028)^{\circ}$ $(0.227)^{\circ}$ 4 month after Dinaster $(0.016)^{\circ}$ $(0.019)^{\circ}$ $(0.028)^{\circ}$ 5 month after Dinaster $(0.016)^{\circ}$ $(0.109)^{\circ}$ $(0.027)^{\circ}$ 6 month after Dinaster $(0.011)^{\circ}$ $(0.009)^{\circ}$ $(0.008)^{\circ}$ 7 month after Dinaster $(0.013)^{\circ}$ $(0.009)^{\circ}$ $(0.008)^{\circ}$ 7 month after Dinaster $(0.133)^{\circ}$ $(0.111)^{\circ}$ $(0.009)^{\circ}$ $(0.003)^{\circ}$ 9 month after Dinaster $(0.133)^{\circ}$ $(0.111)^{\circ}$ $(0.003)^{\circ}$ 10 month after Dinaster $(0.183)^{\circ}$ $(0.176)^{\circ}$ $(0.183)^{\circ}$ 10 month after Dinaster $(0.183)^{\circ}$ $(0.176)^{\circ}$	Month of Disaster	.0154	.0154	.0147	.0150
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	1 month after Disaster	.0180*	.0171*	.0161*	.0158*
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0103)	(.0102)	(.0095)	(.0090)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	2 month after Disaster	.0206**	.0185**	.0178** (0095)	.0168**
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	3 month after Disaster	.0242**	.0219**	.0215**	.0200**
International nucley Disaster (210)	4 month often Disenter	(.0109)	(.0097)	(.0093)	(.0086)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	4 month after Disaster	(.0116)	(.0100)	(.0101)	(.0091)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	5 month after Disaster	.0215*	.0190**	.0199**	.0178*
0 Disset (0111) 10094 0009 (0099) (0099) 7 month after Disaster (0108) (0098) (0101) (0092) 8 month after Disaster $(0177)^*$ $(0181^*$ (0172^*) (0181^*) (0172^*) 9 month after Disaster (0173^*) (0184^*) (0172^*) (0183^*) 10 month after Disaster (0117) (0184^*) (0172^*) (0183^*) 11 month after Disaster (0110) (0116) (0102) (0183^*) 12 month after Disaster (0114) (0110) (0106) (0106) 6 month after Disaster (0114) (0104) (0099) (0106) 4 month after Disaster (0100) (0101) (0103) (0103) 14 month after Disaster (0100) (0103) (0103) 15 month after Disaster (0107) (0133) (0132) 14 month after	6 month ofter Disaster	(.0115)	(.0095)	(.0100)	(.0090)
7 month after Disaster $.0201^{*}$ $.0183^{*}$ $.0200^{*}$ $.0187^{**}$ 8 month after Disaster $.0183^{*}$ $.0179^{*}$ $.0184^{*}$ $.0179^{*}$ 9 month after Disaster $.0173^{*}$ $.0181^{*}$ $.0174^{*}$ $.0099$ 10 month after Disaster $.0173^{*}$ $.0181^{*}$ $.0174^{*}$ $.0099$ 11 month after Disaster $.0.0101$ $.0.0160$ $.0.076^{*}$ $.0183^{*}$ 12 month after Disaster $.0.019^{*}$ $.0.0160$ $.0.0176^{*}$ $.0.0183^{*}$ 6 month after Disaster $.0.019^{*}$ $.0.013^{*}$ $.0.012^{*}$ $.0.016^{*}$ 4 month shefore Disaster $.0.012^{*}$ $.0.010^{*}$ $.0.013^{*}$ 5 month after Disaster $.0.012^{*}$ $.0.010^{*}$ $.0.010^{*}$ 4 month after Disaster $.0.011^{*}$ $.0.013^{*}$ $.0.013^{*}$ 13 month after Disaster $.0.011^{*}$ $.0.010^{*}$ $.0.009^{*}$ 14	o month after Disaster	(.0111)	(.0094)	(.0099)	(.0089)
8 month after Disaster $(.0108)$ $(.0109)$ $(.0101)$ $(.0102)$ 9 month after Disaster $(.0173)^*$ $(.018)^*$ $(.0114)^*$ $(.0179)^*$ 9 month after Disaster $(.0173)^*$ $(.018)^*$ $(.0174)^*$ $(.0079)^*$ 10 month after Disaster $(.0114)$ $(.0104)$ $(.0110)$ $(.0102)$ $(.0105)$ 11 month after Disaster $(.0114)$ $(.0116)$ $(.0102)$ $(.0105)$ 12 month after Disaster $(.0114)$ $(.0111)$ $(.0104)$ $(.0106)$ 6 months before Disaster $(.0100)$ $(.0103)$ $(.0103)$ 4 month after Disaster $(.0100)$ $(.0103)$ $(.0103)$ 14 month after Disaster $(.0103)$ $(.0103)$ $(.0103)$ 15 month after Disaster $(.0107)$ $(.0109)$ $(.0103)$ 14 month after Disaster $(.0017)$ $(.0109)$ $(.0100)$ 16 month after Disaster $(.0087)$ <td< td=""><td>7 month after Disaster</td><td>.0201*</td><td>.0187*</td><td>.0200*</td><td>.0187**</td></td<>	7 month after Disaster	.0201*	.0187*	.0200*	.0187**
0 month after Disaster (.0107) (.0108) (.0102) (.0099) 9 month after Disaster .0113' .01174' .0173'' .0109'' 10 month after Disaster .0114' .0104'' .0107'' .0189'' 11 month after Disaster .0115' .0182'' .0166 .0176'' .0183'' 12 month after Disaster .0110' (.0110) (.0111) (.0104) (.0105) 12 month after Disaster .0113' .0113' .0113' .0113'''''' 6 months before Disaster .0102 .0100'''''' .0183''' .0113'''''''''''''''''''''''''''''''''''	8 month after Disaster	(.0108) 0183*	(.0098)	(.0101) 0184*	(.0092) 0179*
9 month after Disaster .0173* .0181* .0174* .0173* 10 month after Disaster .0184* .0194* .0175 .0189* 11 month after Disaster .0175 .0182 .0166 .0176* .01010 .01101 .0102 .0105 .0183* .0111 .0112 .0166 .0176* .0183* .0111 .0111 .01010 .01161 .01061 6 months before Disaster .0101 .01013 .01013 5 months before Disaster .0101 .01013 .01013 13 month after Disaster .01011 .01013 .01013 14 month after Disaster .01013 .0113 .01013 15 month after Disaster .01016 .0113 .01013 16 month after Disaster .0116 .0113 .01013 16 month after Disaster .0116 .0113 .0102 17 month after Disaster .0016 .00097 .00089 16 month after Disaster .0018 .0012 .00083	o month after Disaster	(.0107)	(.0108)	(.0102)	(.0099)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	9 month after Disaster	.0173*	.0181*	.0174*	.0179*
11 month after Disaster (0104) (0111) (0006) (0006) 11 month after Disaster (0110) (0116) (0102) (0103) 12 month after Disaster $(0188^{*}$ (0113) (0110) (0113) 6 months before Disaster (0114) (0111) (0104) (0009) 5 months before Disaster (0100) (0100) (0101) 4 month after Disaster (0100) (0103) (0103) 13 month after Disaster (0102) (0103) (0103) 14 month after Disaster (0106) (0009) (0100) 14 month after Disaster (0100) (0009) (0100) 15 month after Disaster (0106) (0009) (0100) 16 month after Disaster (00057) (0009) (0109) 16 month after Disaster (00053) (00091) (0088) 17 month after Disaster (00053) (00092) (0063) 18 month after Disaster (00063) (00083) (0088)	10 month after Disaster	(.0098) .0184*	(.0104) .0194*	(.0092)	(.0093) .0189*
11 month after Disaster .0175 .0182 .0166 .0176* 12 month after Disaster .0189* .0186* .0176* .0183* 6 months before Disaster .0113 .0111 .0102 .0106) 6 months before Disaster .0102 .0103 .0101 7 month stefore Disaster .0102 .0101 .0101 13 month after Disaster .0101 .0103 .0103 14 month stefore Disaster .0101 .0103 .0133 13 month after Disaster .0106 .01011 .0103 14 month after Disaster .0113 .0133 .0132 15 month after Disaster .0117 .0113 .0109 16 month after Disaster .0017 .0062 .0067 17 month after Disaster .0063 .0063 .0063 19 month after Disaster .0063 .0063 .0063 20 month after Disaster .0063 .0063 .0063 21 month after Disaster .0063 .0063 .0063 22 month after Disaster .0063 .0063 .0063 22	month drift Disastel	(.0104)	(.0111)	(.0096)	(.0099)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	11 month after Disaster	.0175	.0182	.0166	.0176*
(.0114) $(.0111)$ $(.0104)$ $(.0106)$ 6 months before Disaster $(.0104)$ $(.0104)$ $(.0106)$ 5 months before Disaster $(.0100)$ $(.0101)$ $(.00099)$ 4 months before Disaster $(.0100)$ $(.0101)$ $(.0103)$ 13 month after Disaster $(.0160)$ $(.0103)$ $(.0103)$ 14 month after Disaster $(.0106)$ $(.0103)$ $(.0103)$ 15 month after Disaster $(.0106)$ $(.0109)$ $(.0111)$ 15 month after Disaster $(.0107)$ $(.0109)$ $(.0109)$ 16 month after Disaster $(.0111)$ $(.0103)$ $(.0109)$ 16 month after Disaster $(.0111)$ $(.0109)$ $(.0109)$ 17 month after Disaster $(.00087)$ $(.0099)$ $(.0098)$ 18 month after Disaster $(.0089)$ $(.0008)$ $(.0083)$ $(.0088)$ 20 month after Disaster $(.0033)$ $(.0081)$ $(.0083)$ $(.0081)$ 21 month after Disaster $(.0033)$ $(.0081)$ $(.0079)$ $(.0079)$ <td>12 month after Disaster</td> <td>(.0110)</td> <td>(.0116)</td> <td>(.0102)</td> <td>(.0105)</td>	12 month after Disaster	(.0110)	(.0116)	(.0102)	(.0105)
6 months before Disaster .0113 .0111 6 months before Disaster .0102 .0105 14 months before Disaster .0008 .0101 13 month after Disaster .0161 .0103 .0103 14 month after Disaster .0161 .0153 .0103 14 month after Disaster .0138 .0133 .0132 15 month after Disaster .0117 .0113 .0109 16 month after Disaster .0017 .0099) .00098 17 month after Disaster .0017 .0099) .00098 17 month after Disaster .0064 .0072 .0067 18 month after Disaster .0064 .0072 .0068 19 month after Disaster .0063 .00083 .0088 20 month after Disaster .0035 .0048 .0063 21 month after Disaster .0035 .0048 .0066 22 month after Disaster .0083 .0068 .0066 23 month after Disaster .0043 .00077 .0049 24 month after Di		(.0114)	(.0111)	(.0104)	(.0106)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	6 months before Disaster		.0113		.0111
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	5 months before Disaster		.0102		.0105
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			(.0100)		(.0101)
13 month after Disaster $(0.161')$ (0.153) (0.155) 14 month after Disaster (0.102) (0.010) (0.103) 15 month after Disaster 0.138 0.133 0.132 16 month after Disaster 0.017 0.113 0.119 16 month after Disaster 0.0090 (0.009) (0.009) 17 month after Disaster 0.0057 0.0062 0.0057 18 month after Disaster 0.064 0.072 0.0063 19 month after Disaster 0.063 0.0063 0.0063 20 month after Disaster 0.0064 0.0022 (0.088) 21 month after Disaster 0.0063 0.0063 0.0063 22 month after Disaster 0.0044 0.0083 (0.081) 21 month after Disaster 0.0044 0.0077 (0.0083) 24 month after Disaster 0.0043 0.0057 (0.0081) 24 month after Disaster (0.017) (0.0077) (0.0077) 12 months before Disaster (0.013) (0.013) 9 months before Disaster (0.0130) $(0.003$	4 months before Disaster		.0098		.0101 (.0103)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	13 month after Disaster		.0161	.0153	.0155
14 month after Disaster 0.0135 0.0132 15 month after Disaster 0.0117 0.013 0.0109 16 month after Disaster 0.0117 0.013 0.0109 17 month after Disaster 0.013 0.020 0.0121 17 month after Disaster 0.057 0.062 0.0577 18 month after Disaster 0.057 0.062 0.0577 19 month after Disaster 0.064 0.072 0.0687 19 month after Disaster 0.064 0.002 0.0633 20 month after Disaster 0.064 0.0033 0.0080 21 month after Disaster 0.0041 0.0488 22 month after Disaster 0.033 0.0080 22 month after Disaster 0.0043 0.0081 23 month after Disaster 0.0043 0.0081 24 month after Disaster 0.0043 0.0081 24 month sbefore Disaster 0.0043 0.0083 7 months before Disaster 0.0043 0.0083 9 months before Disaster 0.0043 0.0083 10 months before Disaster	14 month ofter Disaster		(.0102)	(.0101)	(.0103)
15 month after Disaster 0.017^{+} 0.013^{+} 0.009^{-} 16 month after Disaster 0.009^{-} 0.009^{-} 0.009^{-} 17 month after Disaster 0.007^{-} 0.002^{-} 0.009^{-} 18 month after Disaster 0.0067^{-} 0.002^{-} 0.0067^{-} 19 month after Disaster 0.0064 0.072^{-} 0.0067^{-} 19 month after Disaster 0.0063 0.0083^{-} 0.0083^{-} 20 month after Disaster 0.003^{-} 0.0083^{-} 0.0083^{-} 21 month after Disaster 0.003^{-} 0.0044^{-} 0.0072^{-} 22 month after Disaster 0.003^{-} 0.0043^{-} 0.0083^{-} 23 month after Disaster 0.0046^{-} 0.0077^{-} 0.0066^{-} 24 month after Disaster 0.0046^{-} 0.0077^{-} 0.0063^{-} 12 months before Disaster 0.0043^{-} 0.0077^{-} 0.0048^{-} 10 months before Disaster 0.0046^{-} 0.0077^{-} 0.0048^{-} 10 months before Disaster 0.0046^{-} 0.0017^{-} 0.0049^{-} 0.0061^{-} 0.0049^{-} </td <td>14 month after Disaster</td> <td></td> <td>(.0106)</td> <td>(.0109)</td> <td>(.0110)</td>	14 month after Disaster		(.0106)	(.0109)	(.0110)
16 month after Disaster $(.0096)$ $(.0099)$ $(.0100)$ 17 month after Disaster $(.0097)$ $(.0098)$ $(.0098)$ 17 month after Disaster $(.0089)$ $(.0098)$ $(.0098)$ 18 month after Disaster $(.0089)$ $(.0093)$ $(.0093)$ 19 month after Disaster $(.0083)$ $(.0092)$ $(.0088)$ 20 month after Disaster $(.0083)$ $(.0083)$ $(.0080)$ 20 month after Disaster $(.0083)$ $(.0083)$ $(.0083)$ 21 month after Disaster $(.0083)$ $(.0083)$ $(.0083)$ 22 month after Disaster $(.0083)$ $(.0083)$ $(.0083)$ 23 month after Disaster $(.0046)$ $.0061$ $.0066$ 24 month after Disaster $(.0079)$ $(.0077)$ $.0066$ 12 months before Disaster $(.0017)$ $(.0017)$ $.0066$ 12 months before Disaster $.0046$ $.0066$ $.0066$ 10 months before Disaster $.0043$ $.0057$ 10 months before Disaster $.0046$ $.00666$ <	15 month after Disaster		.0117	.0113	.0109
17 month after Disaster $(.0097)$ $(.0099)$ $(.0098)$ 17 month after Disaster $.0057$ $.0062$ $.0057$ 18 month after Disaster $.0064$ $.0072$ $.0067$ 19 month after Disaster $.0064$ $.0072$ $.0063$ 19 month after Disaster $.0063$ $.0063$ $.0063$ 20 month after Disaster $.0041$ $.0048$ 21 month after Disaster $.0035$ $.0048$ 21 month after Disaster $.0035$ $.0048$ 21 month after Disaster $.0035$ $.0048$ 22 month after Disaster $.0038$ $.0057$ 24 month after Disaster $.0038$ $.0057$ 24 month after Disaster $.0046$ $.0061$ 24 month after Disaster $.0043$ $.0057$ 12 months before Disaster $.0043$ $.0057$ 12 months before Disaster $.0043$ $.0057$ 10 months before Disaster $.00132$ $.0049$ 10 months before Disaster $.0112$ $.0094$ 10 months before Disaster $.0132$ $.0096$ 10 months	16 month after Disaster		(.0096)	(.0099)	.0100)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(.0097)	(.0099)	(.0098)
18 month after Disaster $(.0039)'$ $(.0039)'$ $(.0039)'$ $(.0039)'$ 19 month after Disaster $(.0093)'$ $(.0092)'$ $(.0083)'$ 20 month after Disaster $(.0083)'$ $(.0083)'$ $(.0083)'$ 20 month after Disaster $(.0083)'$ $(.0083)'$ 21 month after Disaster $(.0083)'$ $(.0081)'$ 21 month after Disaster $(.0083)'$ $(.0081)'$ 22 month after Disaster $.0035'$ $.0048$ 23 month after Disaster $.0038'$ $.0054'$ 24 month after Disaster $.0046'$ $.0061'$ 24 month sefore Disaster $.0043'$ $.0057'$ 12 months before Disaster $.0043'$ $.0066'$ 11 months before Disaster $.0046'$ $.0061'$ 10 months before Disaster $.0046'$ $.0066'$ $(.0110)'$ $.0032'$ $.0049'$ 10 months before Disaster $.0006'$ $.00132'$ $(.0095)'$ $.0132'$ $.0095'$ 6 months before Disaster $.0115'$ $.0132'$ $(.0096)'$ $.00316'$ $.0335'$ $.03326'$	17 month after Disaster		.0057	.0062	.0057
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	18 month after Disaster		.0064	.0072	.0067
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(.0093)	(.0092)	(.0088)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	19 month after Disaster			.0063	.0063
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	20 month after Disaster			.0041	.0048
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	21 month often Discotor			(.0083)	(.0081)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	21 month after Disaster			(.0080)	(.0048)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	22 month after Disaster			.0038	.0054
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	23 month after Disaster			(.0084)	(.0083) 0061
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				(.0079)	(.0078)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	24 month after Disaster			.0043	.0057
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	12 months before Disaster			(.0081)	.0066
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	11 months before Disaster				(.0117) .0049
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	10 months before Disaster				(.0110)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	10 months before Disaster				(.0103)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	9 months before Disaster				.0132 (.0095)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	8 months before Disaster				.0121 (.0094)
$\begin{array}{cccccccc} & & & & & & & & & & & & & & & $	7 months before Disaster				.0115
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Constant	6.2053^{***}	6.1970***	6.1942^{***}	6.1936***
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	MonthxYear*	(.0316) Yes	(.0315) Yes	(.0325) Yes	(10326) Yes
$\begin{array}{ccccccc} \mbox{results} & 1002 & 1002 & 10092 & 10092 \\ \mbox{Overall-R}^2 & 81.0000 & 81.0000 & 81.0000 \\ \mbox{R}^2 & .0062 & .0061 & .0062 & .0060 \\ \mbox{F-test} & .2201 & .2215 & .2213 & .2225 \\ \mbox{log}(likelihood) & . & . & . \\ \mbox{Il} & 718.0802 & 728.1707 & 726.2773 & 734.6715 \\ \end{array}$	Observations No. of countries	10692	10692	10692	10692
R ² .0062 .0061 .0062 .0060 F-test .2201 .2215 .2213 .2225 log(likelihood) .718.0802 728.1707 726.2773 734.6715	Overall-R ²	81.0000	81.0000	81.0000	81.0000
F-test .2201 .2215 .2213 .2225 log(likelihood)	R^2	.0062	.0061	.0062	.0060
ll 718.0802 728.1707 726.2773 734.6715	F-test	.2201	.2215	.2213	.2225
	ll	718.0802	728.1707	726.2773	734.6715

Table 2.5: Baseline Event study regressions

 $\begin{array}{c} \mbox{Standard errors in parentheses} \\ {}^{*} \ p < 0.10, \ {}^{**} \ p < 0.05, \ {}^{***} \ p < 0.01 \end{array}$

Column 1 presents our baseline estimates with 3 leads and 12 lags.

Column 2 extends the number of leads to 6 and the number of lags to 18. Column 3 estimate the baseline specification with only 3 leads and extends the number of lags to 24 and finally in column 4 we include 12 leads and 24 lags.

(1) (2) (3) (3) (4) Remittance PC Remittance PC Remittance PC Remittance PC b/se Derms of trade trend -0043 0043 0043 Terms of trade cycle .0000 .0000 .0000 Remittance PC .0004 .0004 .0004 Rainfall 0019 0019 .0000 Terms of trade cycle .0000 0000 .0000 Compartment (.0012) (.0012) (.0012) Terms of trade trend .0000 .0000 .0000 3 months before Disaster .0112 .0118 .0113 .0203 1 months before Disaster .0128 .0127 .0129 .0190 1 month stefore Disaster .0182* .0182* .0182* .0234* 1 month after Disaster .0182* .0182* .0234* .0236* 1 month after Disaster .024* .0207* .0244* .0236* 1 month after Disaster .0255* .0271** .0236*<		(1)	(2)	(2)	(4)
b/se b/se <t< th=""><th></th><th>(1) Remittance PC</th><th>(2) Remittance PC</th><th>(3) Remittance PC</th><th>(4) Remittance PC</th></t<>		(1) Remittance PC	(2) Remittance PC	(3) Remittance PC	(4) Remittance PC
Terms of trade trend 0043 0043 0043 Terms of trade trend 0043 0043 0043 Terms of trade cycle $.0000$ $.00000$ Rainfall 0019 0019 (.0012) (.0002) (.0002) Temperature - (Celsius) 0000 0000 (.0012) (.0002) (.0002) 3 months before Disaster .0112 .0118 .0113 .0203 2 months before Disaster .0128 .0127 .0129 .0190 (.0098) (.0098) (.0098) (.0112) .0113 .0223* 1 months before Disaster .0128 .0127 .0129 .0190 (.0100) (.0107) (.0110) .0136 .0117) Month of Disaster .0159 .0184 .0182* .0234* (.0104) (.0102) (.0104) (.0124) 2 month after Disaster .0224* .02204* .02207* .0224* .0236** (.0103) (.0108)		h/se	h/se	h/se	h/se
Links of take term Long of take term Long of take term (.0037) (.0037) (.0037) Terms of trade cycle .0000 .0000 Rainfall 0019 0019 (.0012) (.0002) (.0002) Temperature - (Celsius) 0000 0000 (.0002) (.0002) (.0002) 3 months before Disaster .0112 .0118 .0113 .0203 (.0104) (.0104) (.0104) (.0121) 1 months before Disaster .0128 .0127 .0129 .0190 1 months before Disaster .0128 .0127 .0129 .0190 .0110 (.0110) (.0135) .0199 (.0100) (.0107) (.0110) (.0136) .0112 .0110 (.0136) .0121 1 month after Disaster .0128 .0127 .0129 .0199 .0136 1 month after Disaster .0182* .0181* .0138* .0236* .0234* 1 month after Disaster .0243* .0236** .0236* .0291** .01313 3 month after Disaster <td>Terms of trade trend</td> <td>- 0043</td> <td>6/30</td> <td>- 0043</td> <td>6/30</td>	Terms of trade trend	- 0043	6/30	- 0043	6/30
Terms of trade cycle 0000 (0004) (0000) Rainfall -0019 (0012) (0012) Temperature - (Celsius) -0000 -0000 3 months before Disaster 0112 0118 0113 0203 2 months before Disaster 0112 0118 0113 0203 2 months before Disaster 0136 0138 0136 $0221*$ (0098) (0098) (0098) (0098) (0121) 1 months before Disaster 0128 0127 0129 0190 (0097) (0095) (0096) (0110) (0110) (0110) (0110) (0110) (0110) (0112) 1 month after Disaster 0204^* 0207^* 0204^* 0226^* 0238^{**} (0104) (0108) (0108) (0107) (0113) 3 month after Disaster 0225^* 0221^* 0226^* 0338^{**} (0112) (0116) (0112) (0138) 0128^* 4 month after Disaster 0202^* 0221^*	ferms of trade trend	(0037)		(0037)	
Initial of field by the system (.0004) (.0004) Rainfall 0019 0019 (.0012) (.0012) (.0002) Temperature - (Celsius) 0000 0000 (.0002) (.0002) (.0002) 3 months before Disaster .0112 .0118 .0113 .0203 (.0104) (.0104) (.0104) (.0132) 2 2 months before Disaster .0136 .0138 .0136 .0221* (.0097) (.0098) (.0098) (.0096) (.0111) 1 months before Disaster .0128 .0127 .0129 .0190 (.0107) (.0107) (.0110) (.0136) 1 1 month after Disaster .0182* .0181* .0182* .0234* 2 month after Disaster .0204* .0226* .0221** .0106) .0107) .0131 3 month after Disaster .0235** .0243** .0226** .0238** .0221** .0106) .0109) .01616 .0112) .0138) .0164 .0129) 4 month after Disaster .0	Terms of trade cycle	0000		0000	
Rainfall 0019 (.0012) Temperature - (Celsius) 0000 (.0002) 3 months before Disaster .0112 .0113 .0203 2 months before Disaster .0136 .0138 .0136 .0221* (.0009) (.0008) (.0098) (.0121) 2 months before Disaster .0136 .0138 .0136 .0221* (.0098) (.0098) (.0098) (.0121) 1 months before Disaster .0159 .0154 .0159 .0190 (.0097) (.0095) (.0096) (.0117) Month of Disaster .0182* .0181* .0182* .0224* (.0104) (.0107) (.0110) (.0136) .0138 .0128* .0234* 1 month after Disaster .0235* .0224* .0226* .0226* .0238** .0291** (.0108) (.0108) (.0107) (.0131) .0166 .0112) .0138 3 month after Disaster .0259** .0271** .0260** .0338** .0226* (.0110) (.0115) (.0110) (.0136)	forms of trade cycle	(0004)		(0004)	
(0012) (.0012) Temperature - (Celsius) 0000 3 months before Disaster .0112 .0118 .0113 .0203 2 months before Disaster .0112 .0118 .0113 .0203 2 months before Disaster .0136 .0138 .0136 .0221* (.0098) (.0098) (.0098) (.0121) 1 months before Disaster .0128 .0127 .0129 .0190 (.0097) (.0095) (.0096) (.0117) .0119 .0136 Month of Disaster .0182* .0181* .0182* .0234* (.0104) (.0102) (.0104) (.0124) 2 month after Disaster .0235** .024** .0236* .0221* (.0108) (.0108) (.0107) (.0131) .0131 3 month after Disaster .0225** .024* .0226* .0216* (.0106) (.0109) (.0106) (.0129) .0138 5 month after Disaster .0202* .0216* .0203* .0258* (.0110) (.0115) (.0110) (.0136)	Rainfall	0019		0019	
Temperature - (Celsius) 0000 0000 (.0002) (.0002) (.0002) 3 months before Disaster .0112 .0118 .0113 .0203 (.0104) (.0104) (.0113) .0203 2 months before Disaster .0136 .0138 .0136 .0221* (.0098) (.0098) (.0098) (.0121) .0190 1 months before Disaster .0128 .0127 .0129 .0190 (.0097) (.0095) (.0096) (.0117) Month of Disaster .0182* .0181* .0182* .0234* (.0104) (.0107) (.0110) (.0136) (.0124) (.0124) 2 month after Disaster .0204* .0207* .0204* .0234* (.0104) (.0108) (.0108) (.0106) (.0129) 4 month after Disaster .0235** .0243** .0236** .0291** (.0112) (.0116) (.0110) (.0138) .0129 4 month after Disaster .0202* .0216* .0203* .0258* (.0105) (.0111) (.0103)		(.0012)		(.0012)	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Temperature - (Celsius)	0000		0000	
3 months before Disaster (0.012) (0.013) (0.014) (0.014) (0.014) 2 months before Disaster (0.036) (0.0098) (0.0098) $(0.021)^*$ 1 months before Disaster 0.0128 0.0127 0.0129 0.0190 1 months before Disaster 0.0128 0.0127 0.0129 0.0190 Month of Disaster 0.0154 0.0159 0.0199 (0.010) (0.0107) (0.0104) (0.0124) 2 month after Disaster 0.024^* 0.0207^* 0.024^* 0.0236^* 1 month after Disaster 0.024^* 0.0207^* 0.024^* 0.0207^* 0.024^* 0.0256^* 2 month after Disaster 0.0255^* 0.027^* 0.204^* 0.0207^* 0.024^* 0.0258^* 3 month after Disaster 0.0255^* 0.027^* 0.204^* 0.020^* 0.038^* 3 month after Disaster 0.0259^* 0.021^* 0.023^* 0.029^* 0.023^* 0.023^* 0.023^* 0.023^* 0.023^* 0.023^* 0.023^* 0.023^* 0.0258^*	Temperature (constas)	(.0002)		(.0002)	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	3 months before Disaster	.0112	.0118	.0113	.0203
2 months before Disaster .0136 .0138 .0136 .0221* 1 months before Disaster .0128 .0127 .0129 .0190 1 months before Disaster .0128 .0127 .0129 .0190 Month of Disaster .0159 .0154 .0159 .0199 (.0101) (.0107) (.0110) (.0136) .0124 1 month after Disaster .0204* .0207* .0204* .0234* (.0104) (.0102) (.0104) (.0124) 2 month after Disaster .0204* .0207* .0204* .0256* (.0108) (.0108) (.0107) (.0131) 3 month after Disaster .0259** .0271** .0260** .0338** (.01106) (.0109) (.01166) (.0129) (.0138) 5 month after Disaster .029** .0211* .0260** .0338** (.0105) (.0111) (.0136) (.0129) (.0136) (.0129) 7 month after Disaster .0197* .0211* .0198* .0226* (.0103) (.0103) (.0103) ((.0104)	(.0104)	(.0104)	(.0132)
1 months before Disaster (.0098) (.0098) (.0098) (.0121) 1 months before Disaster .0128 .0127 .0129 .0190 (.0097) (.0095) (.0096) (.0117) Month of Disaster .0159 .0154 .0159 .0199 (.0110) (.0107) (.0110) (.0136) 1 month after Disaster .0182* .0181* .0182* .0234* (.0104) (.0102) (.0104) (.0124) 2 month after Disaster .0235** .0243** .0236** .0291** (.0106) (.0109) (.0106) (.0129) (.0138) 3 month after Disaster .0259** .0211* .0260** .0338** (.0112) (.0116) (.0112) (.0138) 5 month after Disaster .0202* .0216* .0203* .0258* (.0105) (.0111) (.0105) (.0129) (.0129) 7 month after Disaster .0197* .0211* .0198* .0252* (.0103) (.0103) (.0129) (.0129) (.0103) (.0129)	2 months before Disaster	.0136	.0138	.0136	.0221*
1 months before Disaster 0128 0127 0129 0190 Month of Disaster 0159 0154 0159 0136 1 month after Disaster 0182^* 0181^* 0182^* 0217 1 month after Disaster 0182^* 0181^* 0182^* 0234^* 1 month after Disaster 0204^* 0207^* 0204^* 0226^* 2 month after Disaster 0204^* 0207^* 0204^* 0226^* 3 month after Disaster 0235^{**} 0243^* 0236^{**} 0291^{**} (0106) (0109) (0106) (0129) 4 month after Disaster 0259^{**} 0271^{**} 0226^{**} 0338^{**} (0112) (0116) (0112) (0138) 0258^* 5 month after Disaster 0202^* 0216^* 0203^* 0258^* (0100) (0115) (0110) (0136) 0129 7 month after Disaster 0197^* 0211^* 0198^* 0266^{**} (0103) (0103) (0103) (0129) 0977 019		(.0098)	(.0098)	(.0098)	(.0121)
(.0097) (.0095) (.0096) (.0117) Month of Disaster .0159 .0154 .0159 .0199 (.0110) (.0107) (.0110) (.0116) (.0116) 1 month after Disaster .0182* .0181* .0182* .0234* (.0104) (.0102) (.0104) (.0124) 2 month after Disaster .0204* .0207* .0204* .0256* (.0108) (.0108) (.0107) (.0131) 3 month after Disaster .0235** .0243** .0266** .0291** (.0106) (.0109) (.0106) (.0129) (.0138) 4 month after Disaster .0259** .0271** .0260** .0338** (.0112) (.0116) (.0112) (.0138) 5 month after Disaster .0197* .0211* .0198* .0266** (.0105) (.0111) (.0105) (.0129) .0136 .0129) 7 month after Disaster .0197* .0211* .0198* .0266** (.0103) (.0103) (.0103) .0129) .0129* .0129* <	1 months before Disaster	.0128	.0127	.0129	.0190
Month of Disaster (015) (015) (015) (015) 1 month after Disaster 0182^* 0181^* 0182^* 0234^* (0104) (0102) (0104) (0124) 2 month after Disaster 0204^* 0204^* 0226^* (0108) (0108) (0107) (0131) 3 month after Disaster 0235^{**} 0243^{**} 0236^{**} 0291^{**} (0106) (0109) (0106) (0112) (0138) 4 month after Disaster 0229^{**} 0271^{**} 0206^{**} 0338^{**} (0112) (0116) (0112) (0138) 5 month after Disaster 0202^* 0216^* 0203^* 0258^* (0110) (0115) (0110) (0136) (0129) 7 month after Disaster 0197^* 0211^* 0198^* 0226^*^* (0103) (0103) (0103) (0129) 0223^* 0191^* 0225^* (0104) (0107) (0103) (0129) 0204^{**} 01104		(.0097)	(.0095)	(.0096)	(.0117)
Intervention of Diagonal for Diagonal	Month of Disaster	.0159	.0154	.0159	.0199
1 month after Disaster 0.182^* 0.0181^* 0.0182^* 0.0182^* 0.0182^* 0.0182^* 0.0234^* 2 month after Disaster 0.204^* 0.0207^* 0.0204^* 0.0256^* $(.0108)$ $(.0108)$ $(.0107)$ $(.0131)$ 3 month after Disaster 0.225^{**} 0.0236^{**} 0.0236^{**} 0.0291^{**} $(.0106)$ $(.0109)$ $(.0106)$ $(.0129)$ 4 month after Disaster 0.0259^{**} 0.021^{**} 0.038^{**} $(.0112)$ $(.0116)$ $(.0112)$ $(.0138)$ 5 month after Disaster 0.020^* $.0216^*$ $.0238^*$ $.0258^*$ $(.0110)$ $(.0115)$ $(.0110)$ $(.0138)$ $.0258^*$ $(.0101)$ $(.0115)$ $(.0110)$ $(.0136)$ $.0258^*$ $(.0105)$ $(.0111)$ $(.0105)$ $(.0129)$ 7 month after Disaster 0.197^* $.0221^*$ $.0252^*$ $(.0103)$ $(.0108)$ $(.0103)$ $(.0129)$ 9 month after Disaster 0.175^* $.0184^*$ $.0170^*$ $.02219^*$		(.0110)	(.0107)	(.0110)	(.0136)
(10104) (10102) (10104) (10102) 2 month after Disaster .0204* .0207* .0204* .0256* (10108) (.0108) (.0107) (.0131) 3 month after Disaster .0235** .0243** .0236** .0291** (.0106) (.0109) (.0106) (.0129) 4 month after Disaster .0259** .0271** .0266** .0338** (.0112) (.0116) (.0112) (.0138) 5 month after Disaster .0202* .0216* .0203* .0258* (.0110) (.0115) (.0110) (.0136) 6 6 month after Disaster .0197* .0211* .0198* .0266** (.0105) (.0111) (.0103) (.0129) 7 month after Disaster .0197* .0203* .0191* .0252* (.0103) (.0104) (.0103) (.0129) 9 month after Disaster .0169* .0174* .0176* .0243* (.0104) (.0107) (.0104) (.0129) .0191* 9 month after Disaster .0169* .01	1 month after Disaster	.0182*	.0181*	.0182*	.0234*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0104)	(.0102)	(.0104)	(.0124)
Internal activation(a)101(a)101(a)101(a)101(a)108(a)108(a)107(a)1313 month after Disaster 0.235^{**} 0.243^{**} 0.236^{**} 0.291^{**} (a)106(a)109(a)106(a)129(a)1384 month after Disaster 0.259^{**} 0.271^{**} 0.260^{**} 0.338^{**} (a)112(a)116(a)112(a)1385 month after Disaster 0.202^{*} 0.216^{*} 0.203^{*} 0.258^{*} (a)110(a)115(a)110(a)136(a)1366 month after Disaster 0.197^{*} 0.211^{*} 0.0198^{*} 0.266^{**} (a)105(a)111(a)105(a)110(a)129(a)1297 month after Disaster 0.190^{*} 0.203^{*} 0.191^{*} 0.252^{*} (a)103(a)103(a)103(a)129(a)129(a)1318 month after Disaster 0.175^{*} 0.184^{*} 0.176^{*} 0.243^{*} (a)104(a)107(a)104(a)103(a)1299 month after Disaster 0.169^{*} 0.174^{*} 0.170^{*} 0.221^{*} (a)104(a)104(a)104(a)104(a)12611 month after Disaster 0.177 0.177 0.178 0.191 (a)111(a)111(a)111(a)137(a)140(a)14012 month after Disaster 0.192^{*} 0.191^{*} 0.093^{*} 0.218 (a)115(a)114(a)115(a)140(a)14012 mo	2 month after Disaster	.0204*	.0207*	.0204*	.0256*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0108)	(.0108)	(.0107)	(.0131)
$(.0106)$ $(.0106)$ $(.0109)$ $(.0106)$ $(.0129)$ 4 month after Disaster $.0259^{**}$ $.0271^{**}$ $.0260^{**}$ $.0338^{**}$ $(.0112)$ $(.0116)$ $(.0112)$ $(.0138)$ 5 month after Disaster $.0202^{*}$ $.0216^{*}$ $.0203^{*}$ $.0258^{*}$ $(.0110)$ $(.0115)$ $(.0110)$ $(.0136)$ 6 month after Disaster $.0197^{*}$ $.0211^{*}$ $.0198^{*}$ $.0266^{**}$ $(.0105)$ $(.0111)$ $(.0105)$ $(.0129)$ 7 month after Disaster $.0190^{*}$ $.0203^{*}$ $.0191^{*}$ $.0252^{*}$ $(.0103)$ $(.0103)$ $(.0103)$ $(.0129)$ 8 month after Disaster $.0175^{*}$ $.0184^{*}$ $.0176^{*}$ $.0243^{*}$ $(.0104)$ $(.0107)$ $(.0104)$ $(.0129)$ 9 month after Disaster $.0169^{*}$ $.0174^{*}$ $.0170^{*}$ $.0219^{*}$ $(.0097)$ $(.0098)$ $(.0097)$ $(.0119)$ 10 month after Disaster $.0183^{*}$ $.0185^{*}$ $.0184^{*}$ $.0224^{*}$ $(.0104)$ $(.0104)$ $(.0104)$ $(.0126)$ 11 month after Disaster $.0192^{*}$ $.0191^{*}$ $.0218$ $(.0115)$ $(.0111)$ $(.0111)$ $(.0137)$ 12 month after Disaster $.0192^{*}$ $.0191^{*}$ $.0218^{*}$ $(.0115)$ $(.0114)$ $(.0115)$ $(.0140)$ Exchange rate $.0001$ $.0001$ $.0001$ $(.0007)$ $(.0007)$ $(.0007)$	3 month after Disaster	.0235**	.0243**	.0236**	.0291**
4 month after Disaster $(025)^*$ $(0271^{**}$ (0260^{**}) (0338^{**}) 5 month after Disaster (0202^*) (0216^*) (0238^*) (0258^*) 5 month after Disaster (0202^*) (0216^*) (0203^*) (0258^*) 6 month after Disaster (0110) $(.0115)$ $(.0110)$ $(.0136)$ 6 month after Disaster $.0197^*$ $.0211^*$ $.0198^*$ $.0266^{**}$ $(.0105)$ $(.0111)$ $(.0105)$ $(.0129)$ 7 month after Disaster $.0190^*$ $.0203^*$ $.0191^*$ $.0252^*$ $(.0103)$ $(.0108)$ $(.0103)$ $(.0129)$ 8 month after Disaster $.0175^*$ $.0184^*$ $.0176^*$ $.0243^*$ $(.0104)$ $(.0107)$ $(.0104)$ $(.0129)$ 9 month after Disaster $.0169^*$ $.0174^*$ $.0170^*$ $.0219^*$ $(.0097)$ $(.0098)$ $(.0097)$ $(.0119)$ $(.0126)$ 11 month after Disaster $.0177$ $.0177$ $.0178$ $.0191$ $(.0111)$ $(.0111)$ $(.0113)$ $(.0114)$ </td <td></td> <td>(.0106)</td> <td>(.0109)</td> <td>(.0106)</td> <td>(.0129)</td>		(.0106)	(.0109)	(.0106)	(.0129)
100111 artor Disaster 100112 (.0112) (.0116) (.0112) (.0138) 5 month after Disaster .0202* .0216* .0203* .0258* (.0110) (.0115) (.0110) (.0136) 6 month after Disaster .0197* .0211* .0198* .0266** (.0105) (.0111) (.0105) (.0129) 7 month after Disaster .0190* .0203* .0191* .0252* (.0103) (.0108) (.0103) (.0129) 8 month after Disaster .0175* .0184* .0176* .0243* (.0104) (.0107) (.0104) (.0129) 9 month after Disaster .0169* .0174* .0170* .0219* (.0097) (.0098) (.0097) (.0119) 10 month after Disaster .0183* .0185* .0184* .0224* (.0104) (.0104) (.0104) (.0126) .0111 .0111) .0121* 11 month after Disaster .0177 .0178 .0191 .0137 .0218 .0218 .0218 .0218 .0214* .0214**	4 month after Disaster	.0259**	.0271**	.0260**	.0338**
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0112)	(.0116)	(.0112)	(.0138)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	5 month after Disaster	.0202*	.0216*	.0203*	.0258*
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0110)	(.0115)	(.0110)	(.0136)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	6 month after Disaster	$.0197^{*}$.0211*	.0198*	.0266**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0105)	(.0111)	(.0105)	(.0129)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	7 month after Disaster	.0190*	.0203*	.0191*	.0252*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0103)	(.0108)	(.0103)	(.0129)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	8 month after Disaster	.0175*	.0184*	.0176*	.0243*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0104)	(.0107)	(.0104)	(.0129)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	9 month after Disaster	.0169*	.0174*	.0170*	.0219*
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0097)	(.0098)	(.0097)	(.0119)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	10 month after Disaster	.0183*	.0185*	.0184*	.0224*
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0104)	(.0104)	(.0104)	(.0126)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	11 month after Disaster	.0177	.0177	.0178	.0191
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0111)	(.0111)	(.0111)	(.0137)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	12 month after Disaster	.0192*	.0191*	.0193*	.0218
Exchange rate .0001 .0001 (.0007) (.0007) Unemployment rate		(.0115)	(.0114)	(.0115)	(.0140)
(.0007) (.0007) Unemployment rate 0122**	Exchange rate	· · · ·	.0001	.0001	· · · ·
Unomployment rate 0204^{***} 0122^{**}	-		(.0007)	(.0007)	
	Unemployment rate		0204***	0122**	
(.0043) (.0059)	1 0		(.0043)	(.0059)	
Constant 6.5738*** 6.4224*** 6.7000*** 5.4073***	Constant	6.5738^{***}	6.4224***	6.7000***	5.4073^{***}
(.3077) $(.1357)$ $(.2815)$ $(.0394)$		(.3077)	(.1357)	(.2815)	(.0394)
MonthxYear* Yes Yes Yes Yes	MonthxYear*	Yes	Yes	Yes	Yes
Observations 10692 10692 10692 7128	Observations	10692	10692	10692	7128
No. of countries 81 81 81 54	No. of countries	81	81	81	54
$Overall-R^2$.0156 .0062 .0156 .0345	$Overall-R^2$.0156	.0062	.0156	.0345
\mathbb{R}^2 .2297 .2202 .2298 .1915	\mathbb{R}^2	.2297	.2202	.2298	.1915

Table 2.6: Baseline Event study regressions

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01


Figure 2.6: Dynamic response of Remittance to Disaster





Figure 2.8: Dynamic response of Remittance to Disaster controlling for past and future disasters







Figure 2.9: Dynamic response of Remittance to Disaster controlling for past and future disasters

Figure 2.10: Dynamic response of Remittance to Disaster controlling for past and future disasters with Binned end points





Figure 2.11: Dynamic response of Remittance to Disaster by type

Figure 2.12: Dynamic response of Remittance to Disaster by nature of disaster



(a) Slow Disasters



(b) Sudden Disasters

		/ = \	/ = \	
	(1) Remittance PC b/se	(2) Remittance PC b/se	(3) Remittance PC b/se	(4) Remittance PC b/se
6 months before Disaster	5750	.0080	57.00	.0087
5 months before Disaster		(.0116) 0053		(.0121) 0058
		(.0126)		(.0135)
4 months before Disaster		.0033		.0035
3 months before Disaster	.0050	.0076	.0066	.0078
	(.0123)	(.0128)	(.0125)	(.0137)
2 months before Disaster	(.0070)	(.0133)	(.0128)	(.0100)
1 months before Disaster	.0083	.0103	.0095	.0106
Month of Disaster	(.0116)	(.0128)	(.0121)	(.0134)
Wolten of Disaster	(.0124)	(.0136)	(.0127)	(.0137)
1 month after Disaster	.0179	.0171	.0170	.0171
2 month after Disaster	.0208*	.0129)	.0188*	.0124)
	(.0119)	(.0122)	(.0112)	(.0116)
3 month after Disaster	$.0238^{-1}$	$.0212^{*}$ (0120)	$.0218^{*}$.0211* (.0115)
4 month after Disaster	.0243*	.0219*	.0226**	.0219*
5 month often Disenter	(.0123)	(.0114)	(.0113)	(.0110)
o month after Disaster	(.0124)	(.0182	(.0114)	(.0183
6 month after Disaster	.0232*	.0225**	.0229**	.0224**
7 month after Disaster	(.0119) .0215*	(.0106)	(.0112) .0219*	(.0105) .0220**
	(.0115)	(.0106)	(.0111)	(.0107)
8 month after Disaster	.0219*	.0235**	.0225**	.0231**
9 month after Disaster	.0216**	.0236**	.0222**	.0233**
	(.0103)	(.0111)	(.0100)	(.0106)
10 month after Disaster	.0215** (.0106)	.0232** (.0117)	.0215**	.0227***
11 month after Disaster	.0195*	.0206*	.0192*	.0202*
12 month ofter Dianator	(.0111)	(.0120)	(.0107) 0212^*	(.0114) 0217*
12 month after Disaster	(.0113)	(.0115)	(.0108)	(.0112)
13 month after Disaster		.0178*	.0174*	.0175
14 month after Disaster		(.0107) .0168	(.0104) .0168	(.0106) .0166
		(.0112)	(.0112)	(.0114)
15 month after Disaster		.0161	.0162	.0155
16 month after Disaster		.0157	.0160	.0152
17 month after Disaster		(.0099)	(.0100)	(.0098)
		(.0093)	(.0096)	(.0093)
18 month after Disaster		.0091	.0096	.0090
19 month after Disaster		(.0093)	.0101	.0101
			(.0087)	(.0083)
20 month after Disaster			(.0085)	(.0082)
21 month after Disaster			.0068	.0076
22 month after Disaster			(.0081)	(.0083)
			(.0081)	(.0083)
23 month after Disaster			.0067 (.0074)	.0075 (.0075)
24 month after Disaster			.0047	.0051
12 months before Disaster			(.0071)	(.0071) 0063
				(.0103)
11 months before Disaster				.0055
10 months before Disaster				.0075
9 months before Disaster				(.0092) .0100
8 months before Disaster				(.0098) .0079
7 months before Disaster				(.0111) .0094
Constant	6.1711***	6.1608***	6.1566***	(.0111) 6.1563^{***}
Monthy Vear*	(.0344) Voc	(.0370) Noc	(.0384) Voc	(.0385) Voc
Observations	10692	10692	10692	10692
No. of countries	81	81	81	81
Overall-R ² B ²	.0056	.0053	.0053	.0051
11	.4403	.4440	.4440	.4434

Table 2.7: Baseline Event study regressions controlling for past and future disasters

 $\begin{array}{l} \mbox{Standard errors in parentheses} \\ {}^{*} \ p < 0.10, \ {}^{**} \ p < 0.05, \ {}^{***} \ p < 0.01 \end{array}$

Column 1 presents our baseline estimates with 3 leads and 12 lags.

Column 2 extends the number of leads to 6 and the number of lags to 18. Column 3 estimate the baseline specification with only 3 leads and extends the number of lags to 24 and finally in column 4 we include 12 leads and 24 lags.

$\begin{array}{c c c c c c c c c c c c c c c c c c c $		(1)	(0)	(0)	(4)
Remittance PC Remittance PC Remittance PC Remittance PC Remittance PC Remittance PC b/se		(1)	(2)	(3)	(4)
b/se b/se b/se b/se Terms of trade trend ~ 4332 ~ 4372 Terms of trade cycle 0.015 0.112 (1434) (0.013) (0.013) Terms of trade cycle (0.013) (0.002) Irain -0.022^{*} -0.0000 (0013) (0.012) (0.002) 3 months before Disaster 0.056 0.052 0.057 (0120) (0.124) (0.120) (0.163) 2 months before Disaster 0.052 0.071 0.084 0.011 1 months before Disaster 0.0062 0.0144 (0.121) (0.163) 1 month shefore Disaster 0.026 0.184 0.207 0.286^{*} (0.120) (0.120) (0.121) (0.150) (0.151) 1 month after Disaster 0.224^{**} 0.249^{**} 0.339^{**} (0.120) (0.120) (0.121) (0.150) 2 month after Disaster 0.224^{**} 0.224^{**} 0.339^{**}		Remittance PC	Remittance PC	Remittance PC	Remittance PC
Terms of trade trend 4383 4372 (3184) (3177) Terms of trade cycle .0105 .0112 (and 5) .0112 .0022* (and 5) .0022* .0022* (and 5) .0000 .00000 3 months before Disaster .0056 .0052 .0057 .0138 (and 120) (.0124) (.0120) (.0163) 2 months before Disaster .0082 .0071 .0083 .0152 (and 120) (.0124) (.0121) (.0163) 1 months before Disaster .0100 .0084 .0101 .0171 (.0126) (.0127) (.0160) (.0150) 1 month after Disaster .0206 .0184 .0207 .0286* (.0120) (.0120) (.0121) (.0150) .0151) 2 month after Disaster .0202* .0207* .0230** .0339** (.0120) (.0121) (.0121) (.0150) .033** 2 month after Disaster .0220* .0224* .0325** .0355** (.0121) (.0121)<		b/se	b/se	b/se	b/se
(.3184) (.3177) Terms of trade cycle (.0105 0.0112 (.0454) (.0459) Irain 0022* 0002 Irain (.0013) (.0013) Temperature - (Celsius) 0000 0000 3 months before Disaster .0056 .0052 .0057 2 months before Disaster .0082 .0071 .0083 .0152 1 months before Disaster .0026 .0184 .0010 .0171 Month of Disaster .0206 .0184 .0207 .0286* (.0120) (.0121) (.0127) (.0160) 1 month after Disaster .0206 .0184 .0207 .0286* (.0120) (.0121) (.0121) (.0151) .0115) 2 month after Disaster .0220* .0209* .0222* .0307** (.0120) (.0121) (.0151) .0153) 4 month after Disaster .0220* .0224* .0239* .0336** (.0121) .0124 .0121	Terms of trade trend	4383		4372	
Terms of trade cycle .0105 .0112 (.0454) (.0459) Irain 0022* 0022* Temperature - (Celsius) .0000 .00000 3 months before Disaster .0056 .0057 .0138 (.0120) (.0124) (.0120) (.0163) 2 months before Disaster .0052 .0057 .0163) 1 months before Disaster .0082 .0071 .0083 .0152 (.0121) (.0124) (.0121) (.0163) 1 months before Disaster .0100 .0084 .0101 .0171 (.0115) (.0116) (.0115) (.0160) 1 month after Disaster .0206 .0184 .0207 .0286* (.0120) (.0120) (.0121) (.0150) .0151) 2 month after Disaster .0202* .0207* .0248* .033** 1 month after Disaster .0224* .0240* .0249* .0238* 1 month after Disaster .0233* .0246 .0252** .0356** (.0121) (.0124) (.0121) (.0150) <t< td=""><td></td><td>(.3184)</td><td></td><td>(.3177)</td><td></td></t<>		(.3184)		(.3177)	
$(.0454)$ $(.0459)$ Irain 0022^* 0003 Temperature - (Celsius) 0000 0000 3 months before Disaster $.0056$ 0052 0000 2 months before Disaster 0056 0052 0037 0138 2 months before Disaster 0052 0071 0088 0152 1 months before Disaster 0124 $(.0121)$ $(.0124)$ $(.0121)$ $(.0163)$ 1 months before Disaster 0206 0184 0207 0286° $(.0126)$ $(.0124)$ $(.0127)$ $(.0160)$ 1 month after Disaster 0206° 0184 0207 0288° $(.0120)$ $(.0120)$ $(.0121)$ $(.0150)$ 0339^{*+} $(.0120)$ $(.0120)$ $(.0121)$ $(.0150)$ 3 month after Disaster $.0220^*$ $.0224^*$ $.0234^*$ $.0339^{*+}$ $(.0121)$ $(.0121)$ $(.0121)$ $(.0150)$ 5 month after Disaster	Terms of trade cycle	.0105		.0112	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		(.0454)		(.0459)	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	lrain	0022*		0022*	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		(.0013)		(.0013)	
Interpretation (0002) (0002) (0002) 3 months before Disaster .0056 .0052 .0057 .0138 2 months before Disaster .0082 .0071 .0083 .0152 1 months before Disaster .0000 .0084 .0101 .0171 (.0121) (.0124) (.0121) (.0163) 1 month before Disaster .0000 .0084 .0101 .0171 (.0126) (.0124) (.0127) (.0160) 1 month after Disaster .0206 .0184 .0207 .0288* (.0120) (.0121) (.0151) (.0150) 2 month after Disaster .0220* .0220* .0222* .0337** (.0120) (.0119) (.0120) (.0150) .0356** 3 month after Disaster .0230* .0204* .0228* .0336** (.0121) (.0124) (.0121) (.0150) .0346** (.0121) (.0124) (.0121) (.0151) .0346** (.0121) (.0124) <td>Temperature - (Celsius)</td> <td>- 0000</td> <td></td> <td>- 0000</td> <td></td>	Temperature - (Celsius)	- 0000		- 0000	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Temperature (Censius)	(0002)		(0000)	
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	3 months before Disaster	0056	0052	0057	0138
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	5 months before Disaster	(0120)	(0124)	(0120)	(0162)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2	(.0120)	(.0124)	(.0120)	(.0103)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	2 months before Disaster	.0082	.0071	.0083	.0152
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0121)	(.0124)	(.0121)	(.0163)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	I months before Disaster	.0100	.0084	.0101	.0171
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.0115)	(.0116)	(.0115)	(.0150)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Month of Disaster	.0206	.0184	.0207	$.0286^{*}$
1 month after Disaster .0197 .0181 .0198 .0289* (.0120) (.0120) (.0121) (.0151) 2 month after Disaster .0220* .0209* .0222* .0337** (.0120) (.0119) (.0120) (.0150) 3 month after Disaster .0247** .0240* .0249** .0339** (.0122) (.0124) (.0122) (.0153) 4 month after Disaster .0203* .0246* .0252** .0356** (.0121) (.0124) (.0121) (.0151) 5 month after Disaster .0233* .0234* .0234* .0340** (.0121) (.0124) (.0121) (.0151) 6 month after Disaster .0216* .0217* .0218* .0314** (.0112) (.0113) (.0142) (.0142) 8 month after Disaster .0221** .0216** .0221** .0307** (.0103) (.0103) (.0103) (.0139) .0314** 10 month after Disaster .0221** .0221** .0203* .0323* (.0103) (.0103)		(.0126)	(.0124)	(.0127)	(.0160)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	1 month after Disaster	.0197	.0181	.0198	.0289*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0120)	(.0120)	(.0121)	(.0151)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	2 month after Disaster	.0220*	.0209*	$.0222^{*}$.0307**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0120)	(.0119)	(.0120)	(.0150)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	3 month after Disaster	.0247**	.0240*	.0249**	.0339**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.0122)	(.0124)	(.0122)	(.0153)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	4 month after Disaster	0250**	0246*	0252**	0356**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0121)	(0124)	(0121)	(0150)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	5 month after Disaster	0203*	0204	0204*	0296*
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	5 month after Disaster	(0121)	(0124)	(0121)	(0151)
0 month after Disaster $.0233$ $.0234$ $.0234$ $.0340$ 7 month after Disaster $.0216^*$ $.0217^*$ $.0218^*$ $.0314^{**}$ 8 month after Disaster $.0222^*$ $.0220^*$ $.0223^*$ $.0323^{**}$ $(.0112)$ $(.0115)$ $(.0113)$ $(.0142)$ 8 month after Disaster $.0221^{**}$ $.0220^*$ $.0223^*$ $.0323^{**}$ $(.0112)$ $(.0114)$ $(.0113)$ $(.0139)$ 9 month after Disaster $.0221^{**}$ $.0216^{**}$ $.0222^{**}$ $.0307^{**}$ $(.0103)$ $(.0103)$ $(.0103)$ $(.0128)$ 10 month after Disaster $.0221^{**}$ $.0221^{**}$ $.0222^{**}$ $.0296^{**}$ $(.0107)$ $(.0106)$ $(.0107)$ $(.0131)$ $(.0128)$ 11 month after Disaster $.0204^*$ $.0196^*$ $.0205^*$ $.0253^*$ $(.0113)$ $(.0111)$ $(.013)$ $(.0141)$ $(.0141)$ 12 month after Disaster $.0230^{**}$ $.0221^*$ $.0231^{**}$ $.0294^{**}$ $(.0007)$ $(.0007)$ $(.0007)$ <td< td=""><td>6 month often Digoston</td><td>(.0121)</td><td>(.0124)</td><td>(.0121)</td><td>(.0101)</td></td<>	6 month often Digoston	(.0121)	(.0124)	(.0121)	(.0101)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	o month after Disaster	.0233	.0254	.0254	.0340
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0110)	(.0120)	(.0110)	(.0144)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	7 month after Disaster	.0216*	.0217*	.0218**	.0314**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0112)	(.0115)	(.0113)	(.0142)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	8 month after Disaster	.0222*	.0220*	.0223*	.0323**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0112)	(.0114)	(.0113)	(.0139)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	9 month after Disaster	.0221**	.0218**	.0221**	$.0307^{**}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0103)	(.0103)	(.0103)	(.0128)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	10 month after Disaster	.0221**	.0216**	.0222**	.0296**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0107)	(.0106)	(.0107)	(.0131)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	11 month after Disaster	.0204*	$.0196^{*}$	$.0205^{*}$.0253*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.0113)	(.0111)	(.0113)	(.0141)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	12 month after Disaster	.0230**	.0221*	.0231**	.0294**
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.0116)	(.0114)	(.0116)	(.0143)
$\begin{array}{c cccccc} & & & & & & & & & & & & & & & & $	Exchange rate	()	.0002	.0001	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			(.0007)	(.0007)	
$\begin{array}{c ccccc} & & & & & & & & & & & & & & & & &$	Unemployment rate		- 0182***	- 0100	
Constant 8.1096^{***} 6.3608^{***} 8.2061^{***} 5.3497^{***} (1.3986) (.1374) (1.3638) (.0434) MonthxYear* Yes Yes Yes Yes Observations 10692 10692 10692 7128 Overall-R ² 81.0000 81.0000 54.0000 R ² 0162 0056 0162 0419	e nemployment rate		(0053)	(0061)	
Constant 8.1090 0.5006 6.2001 5.3497 (1.3986) (1.374) (1.3638) (.0434) MonthxYear* Yes Yes Yes Yes Observations No. of countries 10692 10692 10692 7128 Overall-R ² 81.0000 81.0000 81.0000 54.0000	Constant	S 1006***	6 2608***	(.0001) 8 2061***	5 9407***
MonthxYear* Yes Yes Yes Yes Yes Observations No. of countries 10692 10692 10692 7128 Overall- \mathbb{R}^2 81.0000 81.0000 81.0000 54.0000 \mathbb{R}^2 0162 0056 0162 0410	Constant	(1 2000)	(1974)	(1.2020)	0.0497
Monthy Year** Yes		(1.3980)	(.1374)	(1.3038)	(.0434)
Observations 10692 10692 10692 7128 No. of countries 10692 10692 7128 0056 0162 00162	Monthx Year	res	res	res	res
No. of countries 10692 10692 10692 7128 Overall-R ² 81.0000 81.0000 81.0000 54.0000 R ² 0162 0056 0162 0410	Observations	10000	10000	10000	F 100
Overall- R^2 81.000081.000081.000054.0000 R^2 0162005601620410	No. of countries	10692	10692	10692	7128
P^2 0162 0056 0162 0410	Overall-R ²	81.0000	81.0000	81.0000	54.0000
It .0102 .0000 .0102 .0419	\mathbb{R}^2	.0162	.0056	.0162	.0419
F-test .2361 .2205 .2362 .1961	F-test	.2361	.2205	.2362	.1961
log(likelihood) 829.3934 720.8690 829.9669 191.4838	log(likelihood)	829.3934	720.8690	829.9669	191.4838

Table 2.8:	Event study	$\operatorname{regressions}$	$\operatorname{controlling}$	for	past	and	future	disasters
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Column 1 presents our baseline estimates using our alternative specification for the disaster variable. Column 2 controls for other shocks in the origin country whilst column 3 control for the economic condition in the host country and in column 4 we control for both other shocks and economic conditions jointly. Column 5 presents the results from restricting the sample to only countries with relatively larger stock of immigrants.

	(1)	(2)	(2)	(4)
	(1)	(2)	(3)	(4)
	Remittance PC	Remittance PC	Remittance PC	Remittance PC
	b/se	b/se	b/se	b/se
F3bin _D	0082	0090	0084	0091
1 months hafana Diasatan	(.0114)	(.0111)	(.0114)	(.0112)
1 months before Disaster	.0019	.0023	.0019	.0023
Mouth of Discotory	(.0026)	(.0025)	(.0026)	(.0025)
Month of Disaster	(0120^{+1})	(0057)	(0057)	(0130^{+1})
1 month often Disector	(.0057)	(.0037)	(.0007)	(.0007)
1 month after Disaster	.0115	.0119	.0114	(0052)
2 month ofter Dispeter	(.0000)	(10032)	(.0055)	(.0055)
2 month after Disaster	(0057)	(0057)	(0057)	(0057)
2 month ofter Disaster	(.0037)	(.0037)	(.0057)	(.0057)
5 month after Disaster	.0134	.0134	.0100	.0100
4 month after Disaster	(.0002)	(10002)	(.0003)	(10003)
4 month after Disaster	(0072)	(0073)	(0072)	(0073)
5 month ofter Disaster	(.0072)	(.0073)	(.0072)	(.0075)
5 month after Disaster	(0078)	(0080)	(0078)	.0105
6 month after Disaster	(.0078)	(10080)	(.0078)	(10080)
o month after Disaster	(0084)	(0085)	(0084)	(0085)
7 month after Disaster	(.0034)	(.0085)	(.0034)	(.0085)
7 month after Disaster	(0082)	(0124)	(0082)	(0082)
8 month after Disaster	(10082)	0134	(.0032)	(10082)
o month after Disaster	(0094)	(0093)	(0094)	(0093)
9 month after Disaster	0140	0135	0140	0135
5 month after Disaster	(0094)	(0091)	(0094)	(0091)
10 month after Disaster	0137	0134	0137	0134
	(.0107)	(.0103)	(.0107)	(.0103)
11 month after Disaster	0120	0118	0119	0118
	(.0114)	(.0110)	(.0114)	(.0110)
Binned lag beyond 12 months	0073	0084	0074	0085
	(.0126)	(.0123)	(.0126)	(.0123)
Terms of trade trend	()	4363	()	4350
		(.3157)		(.3147)
Terms of trade cycle		.0106		.0114
		(.0455)		(.0459)
Rainfall		0015		0016
		(.0012)		(.0012)
Temperature - (Celsius)		.0000		.0000
		(.0002)		(.0002)
Exchange rate			.0002	.0001
0			(.0007)	(.0007)
Unemployment rate			0162***	0089
1 0			(.0052)	(.0063)
Constant	6.3079^{***}	8.2543***	6.4741***	8.3372***
	(.2190)	(1.4215)	(.2878)	(1.3893)
MonthxYear*	Yes	Yes	Yes	Yes
Observations	10692	10692	10692	10692
No. of countries	81.0000	81.0000	81.0000	81.0000
$Overall-R^2$.0050	.0124	.0050	.0123
\mathbb{R}^2	.2199	.2355	.2201	.2356
F-test				•
log(likelihood)	716.6602	824.9438	718.1240	825.6104

Table 2.9: Event study regressions with Binned ends

	(1)	(2)	(3)	(4)
	Remittance PC	Remittance PC	Remittance PC	Remittance PC
	h/se	h/se	h/se	b/se
F3bin	0082	0057	0095	0122
1000	(.0114)	(.0094)	(.0112)	(.0110)
1 months before Disaster	.0019	.0011	.0019	.0030
	(.0026)	(.0016)	(.0022)	(.0018)
Month of Disaster	.0120**	.0061	.0056	.0008
	(.0057)	(.0038)	(.0050)	(.0056)
1 month after Disaster	.0113**	.0060*	.0113**	.0139***
	(.0053)	(.0036)	(.0045)	(.0049)
2 month after Disaster	.0130**	.0079*	.0117**	.0118**
	(.0057)	(.0041)	(.0053)	(.0055)
3 month after Disaster	.0154**	.0103**	.0154***	.0158***
	(.0062)	(.0046)	(.0055)	(.0051)
4 month after Disaster	.0157**	.0107**	.0158**	.0177***
	(.0072)	(.0053)	(.0067)	(.0067)
5 month after Disaster	.0111	.0062	.0102	.0121
	(.0078)	(.0052)	(.0074)	(.0078)
6 month after Disaster	.0144*	.0082	.0127	$.0127^{*}$
	(.0084)	(.0063)	(.0079)	(.0073)
7 month after Disaster	.0130	.0072	.0110	.0122*
	(.0082)	(.0065)	(.0073)	(.0066)
8 month after Disaster	.0139	.0075	.0088	.0092
	(.0094)	(.0072)	(.0075)	(.0069)
9 month after Disaster	.0140	.0071	.0117	.0117
	(.0094)	(.0074)	(.0081)	(.0083)
10 month after Disaster	.0137	.0083	.0111	.0083
	(.0107)	(.0089)	(.0086)	(.0073)
11 month after Disaster	.0120	.0070	.0107	.0062
	(.0114)	(.0095)	(.0091)	(.0074)
L12bin	0073	0067	0075	0122
	(.0126)	(.0107)	(.0130)	(.0139)
Constant	6.3079^{***}	6.3326^{***}	6.2900^{***}	6.3070^{***}
	(.2190)	(.2334)	(.1697)	(.1237)
MonthxYear*	Yes	Yes	Yes	Yes
Observations	10692	10692	10692	10692
No. of countries	81	81	81	81
Overall-R ²	.0050	.0040	.0004	.0001
\mathbb{R}^2	.2199	.2201	.2188	.2174

Table 2.10: Robustness tests

Column [1] presents the results from our preferred basic specification, column [2] use the frequency of disasters as the measure of disaster while column [3] and [4] restricts the measure of disaster to disasters on and above 25th percentile and 50th percentile of the share of the population affected by the disaster respectively.

	(1)	(2)	(3)	(4)	(5)
	Remittances	Remittance PC	Remittance PC	Remittances	Remittance P
	b/se	b/se	b/se	b/se	b/se
12 months before disaster	.0091				
	(.0165)				
Disaster	.0087	.0181	.0199	.0081	.0200
	(.0116)	(.0128)	(.0125)	(.0120)	(.0126)
12 months after disaster	.0185				
	(.0144)				
1 to 6 months before disaster		.0075	.0081	.0006	.0082
		(.0142)	(.0153)	(.0139)	(.0153)
1 to 6 months after disaster		.0276	.0269	.0162	.0272
		(.0189)	(.0175)	(.0137)	(.0175)
7 to 12 months after disaster		.0259	.0273	.0193	.0276
		(.0179)	(.0185)	(.0144)	(.0185)
6 to 12 months before disaster			.0089	.0016	.0091
			(.0147)	(.0125)	(.0147)
Terms of trade trend			4312	. ,	4302
			(.3158)		(.3150)
Terms of trade cycle			.0098		.0105
			(.0447)		(.0450)
lrain			0016*		0016*
			(.0009)		(.0009)
Temperature - (Celsius)			.0000		.0000
			(.0002)		(.0002)
Exchange rate			()	0007	.0001
				(.0004)	(.0007)
Unemployment rate				0200***	0103*
e nemproyment rate				(.0045)	(.0062)
Constant	8612***	6 1777***	8 0837***	1 1777***	8 1853***
	(.0215)	(.0363)	(1.3857)	(.0913)	(1.3543)
MonthxYear*	Yes	Yes	Yes	Yes	Yes
Observations	10692	10692	10692	10692	10692
No. of countries	81	81	81	81	81
Overall-B ²	.0104	.0063	.0177	.0142	.0177
R ²	.1552	.2163	.2318	.1622	.2319
F-test		.=100	010		010
log(likelihood)	. 3247.3972	. 691.9280	. 799.2874	3291,8913	799.7666
	5211.0012	001.0100		3-01.0010	

Table 2.11: Event study with efficient specification

	(1)	(2)	(3)
	Remittance PC	Remittance PC	Remittance PC
	b/se	b/se	b/se
F3bin _D	.0058	0024	0217
	(.0152)	(.0261)	(.0181)
1 months before Disaster	0033	.0043	.0014
	(.0032)	(.0066)	(.0035)
Month of Disaster	0002	.0191	.0136**
	(.0084)	(.0144)	(.0050)
1 month after Disaster	0042	.0151	.0142**
	(.0056)	(.0114)	(.0062)
2 month after Disaster	.0008	.0168	.0125***
	(.0055)	(.0150)	(.0039)
3 month after Disaster	.0014	.0212	.0140**
	(.0071)	(.0144)	(.0057)
4 month after Disaster	0010	.0245	.0145**
	(.0073)	(.0169)	(.0064)
5 month after Disaster	0058	.0182	.0111*
	(.0074)	(.0198)	(.0057)
6 month after Disaster	0033	.0205	.0135**
	(.0076)	(.0215)	(.0061)
7 month after Disaster	0002	.0142	.0161**
	(.0081)	(.0194)	(.0076)
8 month after Disaster	.0004	.0142	$.0192^{*}$
	(.0059)	(.0233)	(.0105)
9 month after Disaster	.0002	.0175	$.0165^{**}$
	(.0062)	(.0250)	(.0078)
10 month after Disaster	.0028	.0129	.0193
	(.0074)	(.0280)	(.0117)
11 month after Disaster	.0060	.0120	.0140
	(.0085)	(.0309)	(.0126)
Binned lag beyond 12 months	.0145	0059	0131
	(.0101)	(.0291)	(.0163)
Constant	6.7756^{***}	5.9749^{***}	6.1282^{***}
	(.1756)	(.5351)	(.3002)
MonthxYear*	Yes	Yes	Yes
Observations	2904	3564	4224
No. of countries	22	27	32
Overall-R ²	.0429	.0008	.0383
R^2	.3700	.2194	.2003
F-test		•	•
log(likelihood)	380.5774	120.8161	497.7427
0(/			

Table 2.12: Event study by contry's level of Development

Column [1] presents the results from restricting the sample to the group of lower income countries, column [2] the group of lower middle income countries and column [3] the group of upper middle income countries.

	(1)	(2)	(3)
	Remittance PC	Remittance PC	Remittance PC
	b/se	b/se	b/se
$F3bin_D$	0108	0023	.0047
	(.0149)	(.0060)	(.0052)
1 months before Disaster	.0058	0039	.0048
	(.0035)	(.0033)	(.0051)
Month of Disaster	0006	0051	.0423***
	(.0100)	(.0077)	(.0142)
1 month after Disaster	.0198**	0010	.0076
	(.0082)	(.0056)	(.0064)
2 month after Disaster	.0209**	.0029	.0068
	(.0100)	(.0058)	(.0049)
3 month after Disaster	.0237**	0008	.0142*
	(.0090)	(.0066)	(.0075)
4 month after Disaster	.0284**	0002	$.0142^{*}$
	(.0120)	(.0078)	(.0075)
5 month after Disaster	.0262**	0059	.0069
	(.0129)	(.0083)	(.0072)
6 month after Disaster	.0344**	0043	.0110
	(.0147)	(.0085)	(.0077)
7 month after Disaster	.0325**	0102	.0141*
	(.0136)	(.0083)	(.0079)
8 month after Disaster	.0414**	0122	.0066
	(.0179)	(.0092)	(.0071)
9 month after Disaster	$.0327^{*}$	0126	.0168*
	(.0184)	(.0098)	(.0100)
10 month after Disaster	$.0361^{*}$	0158	.0143
	(.0206)	(.0098)	(.0089)
11 month after Disaster	.0328	0144	.0119
	(.0214)	(.0092)	(.0082)
Binned lag beyond 12 months	.0068	0134*	.0043
	(.0195)	(.0074)	(.0055)
Constant	6.4756^{***}	6.5842^{***}	6.1138^{***}
	(.2721)	(.1123)	(.1012)
MonthxYear*	Yes	Yes	Yes
Observations	3889	2915	3888
No. of countries	81	81	81
Overall-R ²	.0002	.0002	.0000
\mathbb{R}^2	.1225	.3684	.1964
F-test	•	24.1742	47.1115
log(likelihood)	1480.9568	2744.9158	3498.3437

Table 2.13: Event study regressions: Economic phase

Column [1] presents the results from restricting the sample to the period between 2005 and 2008, column [2] restricts the sample to the period between 2009 and 2012 and column [3] restricts the sample to the period between 2013 and 2015.

	(1)	(2)	(3)	(4)	(5)
	Remittance PC				
	b/se	b/se	b/se	b/se	b/se
F3bin	0144	.0143	.0184	.0171	0064
	(.0114)	(.0189)	(.0273)	(.0175)	(.0117)
1 months before Disaster	.0000	.0071	.0054	.0082	.0016
	(.0024)	(.0067)	(.0055)	(.0055)	(.0028)
Month of Disaster	.0062	0037	.0197	.0010	.0129**
	(.0051)	(.0060)	(.0148)	(.0127)	(.0055)
1 month after Disaster	.0064*	.0005	.0186	.0107	.0106*
	(.0038)	(.0061)	(.0142)	(.0091)	(.0055)
2 month after Disaster	.0067*	.0016	$.0306^{*}$.0260**	.0120**
	(.0037)	(.0075)	(.0177)	(.0124)	(.0060)
3 month after Disaster	.0086**	.0046	.0290	.0337**	.0136**
	(.0040)	(.0084)	(.0193)	(.0138)	(.0065)
4 month after Disaster	.0098*	0073	.0310	.0333**	.0149*
	(.0053)	(.0101)	(.0199)	(.0144)	(.0075)
5 month after Disaster	.0036	0130	.0329	$.0247^{*}$.0104
	(.0052)	(.0118)	(.0213)	(.0146)	(.0083)
6 month after Disaster	.0059	0134	.0363	.0288**	.0137
	(.0053)	(.0121)	(.0233)	(.0137)	(.0091)
7 month after Disaster	.0055	0111	.0251	$.0263^{*}$.0118
	(.0060)	(.0131)	(.0229)	(.0143)	(.0088)
8 month after Disaster	.0064	0088	.0288	.0390**	.0108
	(.0077)	(.0145)	(.0261)	(.0169)	(.0095)
9 month after Disaster	.0017	.0087	.0383	.0357	.0132
	(.0070)	(.0269)	(.0290)	(.0252)	(.0098)
10 month after Disaster	.0046	0055	.0393	.0397	.0129
	(.0088)	(.0187)	(.0318)	(.0252)	(.0111)
11 month after Disaster	.0020	0077	.0443	.0373	.0118
	(.0095)	(.0192)	(.0345)	(.0271)	(.0118)
L12bin	0156	0012	.0225	.0019	0049
	(.0120)	(.0194)	(.0345)	(.0258)	(.0132)
Constant	6.3980^{***}	6.2091^{***}	6.0848^{***}	6.1955^{***}	6.2644^{***}
	(.1611)	(.0452)	(.1712)	(.0689)	(.2122)
MonthxYear*	Yes	Yes	Yes	Yes	Yes
Observations	10692	10692	10692	10692	10692
No. of countries	81	81	81	81	81
\mathbb{R}^2	.2187	.2201	.2156	.2170	.2183

Table 2.14: Event study regressions by type of disaster

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Column 1 presents the results from estimating the dynamic response of remittance to the occurrence of climatic disasters. Column 2 presents the results from estimating the dynamic response of remittance to the occurrence of Geophysical disasters. Column 3 presents the results from estimating the dynamic response of remittance to the occurrence of meteorological disasters. Column 4 presents the results from estimating the dynamic response of remittance to the occurrence of slow disasters. Column 5 presents the results from

estimating the dynamic response of remittance to the occurrence of sudden disasters.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Remittance PC	Remittance PC	Remittance PC	Remittance PC	Remittance PC	Remittance PC	Remittance PC
E91:-	D/se	D/se	D/se	D/se	D/se	D/se	D/Se
FSDIND	0084	0079	0084	0085	0093	0084	0088
1 months before Disaster	0018	0018	0018	0015	0020	0015	0016
i montilo boloro bibliotor	(.0025)	(.0026)	(.0025)	(.0025)	(.0025)	(.0025)	(.0025)
Month of Disaster	.0119**	.0112*	.0111*	.0108*	.0120**	.0108*	.0111*
	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)
1 month after Disaster	.0117* [*]	.0103*	.0107**	.0099*́	.0108* [*]	.0098*́	.0102*
	(.0052)	(.0054)	(.0053)	(.0053)	(.0052)	(.0053)	(.0053)
2 month after Disaster	.0125**	.0118**	.0114*	.0109*	.0113*	.0109*	.0111*
	(.0057)	(.0058)	(.0058)	(.0059)	(.0059)	(.0058)	(.0058)
3 month after Disaster	.0149**	.0143**	.0139**	.0134**	.0134**	.0134**	.0137**
	(.0062)	(.0064)	(.0063)	(.0063)	(.0063)	(.0063)	(.0063)
4 month after Disaster	.0147**	.0142*	.0136*	.0129*	.0126*	.0129*	.0132*
	(.0072)	(.0072)	(.0072)	(.0073)	(.0074)	(.0073)	(.0073)
5 month after Disaster	.0097	.0103	.0091	.0086	.0077	.0086	.0087
6 month often Disenter	(.0078)	(.0079)	(.0079)	(.0080)	(.0081)	(.0080)	(.0079)
6 month after Disaster	(0085)	.0125	.0113	(0087)	(0097)	(0086)	.0109
7 month after Disaster	(.0033)	0109	0094	(.0087)	(.0085	(.0080)	0094
7 month after Disaster	(0082)	(0083)	(0083)	(0083)	(0083)	(0083)	(0082)
8 month after Disaster	0120	0121	0105	0103	0097	0103	0103
o month droor Dibdotor	(.0093)	(.0095)	(.0095)	(.0095)	(.0094)	(.0095)	(.0093)
9 month after Disaster	.0120	.0124	.0107	.0103	.0100	.0103	.0102
	(.0094)	(.0096)	(.0095)	(.0097)	(.0094)	(.0097)	(.0094)
10 month after Disaster	.0111	.0125	.0102	.0099	.0098	.0099	.0098
	(.0107)	(.0109)	(.0109)	(.0109)	(.0106)	(.0109)	(.0106)
11 month after Disaster	.0096	.0106	.0085	.0080	.0082	.0080	.0079
	(.0114)	(.0116)	(.0116)	(.0117)	(.0113)	(.0117)	(.0113)
Binned ends	0069	0086	0084	0083	0092	0082	0088
	(.0120)	(.0125)	(.0120)	(.0120)	(.0117)	(.0120)	(.0116)
AGC index=2	.1783*		.1301*	.1510	.1558	.1520	.1574
AGG : 1 8	(.0903)		(.0769)	(.1030)	(.1013)	(.1029)	(.1013)
AGC index=3	0432		0810	0410	0278	0396	0255
Share living in North	(.1212)	2 6107***	2 2952***	2 7584***	2 6470***	2 7612***	2 6510***
Share hving in North		(6918)	(6133)	(6413)	(5650)	(6431)	(5675)
AGCxNorth=1		(10010)	(.0100)	0058	0055	0044	0034
				(.1075)	(.1071)	(.1076)	(.1073)
AGCxNorth=2				0744	0635	0742	0631
				(.0547)	(.0565)	(.0549)	(.0568)
AGCxNorth=3				0917*	0934*	0917*	0935*
				(.0475)	(.0484)	(.0477)	(.0487)
Terms of trade trend					3922		3937
					(.2401)		(.2403)
Terms of trade cycle					.0474		.0467
					(.0401)		(.0406)
Irain					0020*		
Tama antina (Calaina)					(.0011)		
Temperature - (Ceisius)					0000		
Unemployment rate					(.0002)	- 0177***	- 0150**
enemployment fate						(0050)	(0059)
Exchange rate						0001	0001
						(.0006)	(.0007)
Constant	6.2310***	4.7282***	4.8202***	4.5918***	6.4119***	4.8061***	6.5933***
	(.2228)	(.4648)	(.4350)	(.4486)	(1.0758)	(.4698)	(1.0609)
MonthxYear*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10692	10692	10692	10692	10692	10692	10692
No. of countries	81	81	81	81	81	81	81
Overall-R ²	.0990	.2007	.2979	.2917	.2906	.2926	.2984
R ²	.2681	.2955	.3300	.3358	.3482	.3359	.3483

Table 2.15: Efficient specification with AGC and Location

	(1)	(2)	(3)	(4)	(5)	_
	Remittance PC	Remittance PC	Remittance PC	Remittance PC	Remittance PC	
	b/se	b/se	b/se	b/se	b/se	
F3bin _D	0079	0085	0080	0087	0079	
_	(.0105)	(.0106)	(.0106)	(.0103)	(.0106)	
1 months before Disaster	.0021	.0021	.0024	.0028	.0024	
	(.0025)	(.0025)	(.0025)	(.0025)	(.0025)	
Month of Disaster	$.2895^{***}$	$.0493^{**}$	$.2699^{***}$	$.2558^{***}$.2702***	
	(.0953)	(.0215)	(.0847)	(.0815)	(.0848)	
1 month after Disaster	.0105*	.0104*	.0107**	.0115**	.0106**	
	(.0053)	(.0052)	(.0053)	(.0052)	(.0053)	
2 month after Disaster	.0110	.0109	(0050)	$.0113^{\circ}$.0110	
2 month after Disaster	(.0058)	(.0059)	(.0059)	(.0059)	(.0058)	
5 month after Disaster	(0063)	(0064)	(0064)	(0064)	(0064)	
4 month after Disaster	(.0003)	(.0004) 0127*	(1004)	(.0004)	(.0004)	
	(.0073)	(.0075)	(.0075)	(.0076)	(.0075)	
5 month after Disaster	.0083	.0083	.0081	.0074	.0081	
	(.0080)	(.0080)	(.0080)	(.0082)	(.0080)	
6 month after Disaster	.0109	.0101	.0104	.0097	.0104	
	(.0087)	(.0089)	(.0089)	(.0090)	(.0089)	
7 month after Disaster	.0094	.0095	.0095	.0089	.0095	
	(.0083)	(.0083)	(.0083)	(.0083)	(.0083)	
8 month after Disaster	.0103	.0103	.0103	.0098	.0103	
	(.0095)	(.0096)	(.0096)	(.0095)	(.0096)	
9 month after Disaster	.0107	.0101	.0105	.0101	.0105	
10 month often Discotor	(.0097)	(.0099)	(.0099)	(.0096)	(.0099)	
10 month after Disaster	.0107	.0092	.0101	(0100)	.0102	
11 month after Disaster	(.0110)	(.0110)	(.0110)	(.0107)	(.0110)	
	(0117)	(0117)	(0117)	(0113)	(0118)	
Binned lag beyond 12 months	0078	0083	0079	0088	0079	
	(.0119)	(.0121)	(.0120)	(.0117)	(.0120)	
AGC index= 2	.1507	.1596	.1563	.1616	.1574	
	(.1029)	(.1044)	(.1046)	(.1027)	(.1045)	
AGC index=3	0416	0353	0381	0245	0366	
	(.1357)	(.1370)	(.1371)	(.1282)	(.1375)	
Share of immigrant living in North	2.7958^{***}	2.7588^{***}	2.7905^{***}	2.6772^{***}	2.7934^{***}	
	(.6402)	(.6410)	(.6396)	(.5635)	(.6414)	
AGCxNorth=1	0059	0052	0055	0051	0040	
ACC-Nexth 0	(.1074)	(.1073)	(.1073)	(.1069)	(.1074)	
AGCXNorth=2	0735	0751	0742	0634	0740	
ACCyNorth-3	(.0347) 0012*	(.0540)	(.0547)	(.0004)	(.0546)	
AGOXINOITII-5	(0476)	(0476)	(0476)	0955	(0478)	
North*Disaster	4341***	(.0410)	3668**	3397**	3673**	
	(.1468)		(.1462)	(.1414)	(.1464)	
AGCxDisaster=2	()	0567**	0365	0393	0365	
		(.0255)	(.0277)	(.0275)	(.0277)	
AGCxDisaster=3		0255	0126	0148	0126	
		(.0381)	(.0404)	(.0396)	(.0404)	
Terms of trade trend				3912		
				(.2397)		
Terms of trade cycle				.0480		
				(.0402)		
Temperature - (Celsius)				0001		
lugin				(.0002)		
Iram				0010		
Unomployment rate				(.0011)	0201**	
Onemployment fate					(0.087)	
Exchange rate					0001	
					(.0006)	
Constant	4.5597^{***}	4.5866***	4.5615^{***}	6.3777***	4.8030***	
	(.4454)	(.4494)	(.4462)	(1.0729)	(.4847)	
MonthxYear*	Yes	Yes	Yes	Yes	Yes	
Observations	10692	10692	10692	10692	10692	
No. of countries	81	81	81	81	81	
Overall-R ²	.3001	.2899	.2975	.2968	.2984	
R ²	.3371	.3366	.3374	.3496	.3374	

Table 2.16: Efficient specification for determinants of post disaster remittances: AGC

	(1)	(2)	(3)	(4)
	Remittance PC	Remittance PC	Remittance PC	Remittance PC
	b/se	b/se	b/se	b/se
F3bin _D	0091	0086	0093	0093
	(.0112)	(.0115)	(.0112)	(.0112)
1 months before Disaster	.0023	.0024	.0026	.0026
	(.0025)	(.0025)	(.0026)	(.0026)
Month of Disaster	.0130**	0257	1080	1090*
	(.0057)	(.0462)	(.0707)	(.0638)
1 month after Disaster	.0120**	.0118**	.0123**	.0123**
	(.0053)	(.0053)	(.0054)	(.0054)
2 month after Disaster	.0132**	.0131**	.0133**	.0133**
	(.0057)	(.0057)	(.0057)	(.0057)
3 month after Disaster	.0155**	.0153**	.0158**	.0158**
	(.0063)	(.0063)	(.0063)	(.0063)
4 month after Disaster	.0156***	.0153**	.0154***	.0154***
	(.0073)	(.0074)	(.0074)	(.0074)
b month after Disaster	.0105	.0104	.0098	.0098
	(.0080)	(.0081)	(.0079)	(.0079)
b month after Disaster	.0138	.0138	.0135	.0135
	(.0085)	(.0086)	(.0085)	(.0085)
i month after Disaster	.0124	.0120	.0128	.0128
8 months often Director	(.0082)	(.0083)	(.0082)	(.0082)
8 month after Disaster	.0134	.0134	.0129	.0129
0	(.0093)	(.0095)	(.0092)	(.0093)
9 month after Disaster	.0135	.0130	.0127	.0127
10 month often Disseter	(.0091)	(.0094)	(.0090)	(.0090)
10 month after Disaster	.0154	.0137	.0129	.0129
11 month often Disaster	(.0105)	(.0107)	(.0104)	(.0104)
11 month after Disaster	.0118	(0124)	.0125	(0120)
Dinned lag bound 19 months	(.0110)	(.0113)	(.0111)	(.0110)
billined lag beyond 12 months	0085	(0127)	(0123)	0088
Torms of trade trend	(.0125)	(.0127)	(.0125)	(.0122)
Terms of trade trend	(2147)		(2144)	4554
Torms of trade cycle	(.5147)		(.5144)	(.5145)
Terms of trade cycle	(0.0114)		(0458)	(0458)
lrain	- 0016	- 0014	- 0015	- 0015
irain	(0012)	(0012)	(0012)	(0011)
Temperature - (Celsius)	(.0012)	(.0012)	(.0012)	(.0011)
Temperature - (Censius)	(0002)	(0002)	(0002)	(0002)
Unemployment rate	- 0089	- 0154***	- 0026	- 0027
e nempioyment rate	(0063)	(0052)	(0078)	(0081)
Exchange rate	0001	(.0002)	0000	0000
Exchange fate	(.0007)	(.0002)	(.0007)	(.0007)
Disaster*Unemployment rate	(.0044	(10001)	.0002
		(0051)		(0065)
Disaster*Exchange rate		(.0001)	0012	0012
			(.0007)	(.0009)
Constant	8.3372***	6.4731^{***}	8.2775***	8.2782***
	(1.3893)	(.2847)	(1.3925)	(1.3907)
MonthxYear*	Yes	Yes	Yes	Yes
Observations	10692	10692	10692	10692
No. of countries	81	81	81	81
Overall-R ²	.0123	.0048	.0122	.0122
B2	2356	.2203	.2367	.2367

Table 2.17: Efficient	t specification	for de	terminants	of pos	t disaster	remittances
-----------------------	-----------------	--------	------------	--------	------------	-------------

	(1)	(2)	(3)	(4)
	Remittances	Remittances	Remittances	Remittances
pro. nond. n	b/se	b/se	b/se 1527	b/se 1620
prefrenuln	(.0140)	(.0203)	(.1128)	(.1047)
pret rend2n	.0025	0071	.0865	.0872
* U Z	(.0126)	(.0158)	(.0838)	(.0752)
Disaster	.0088	0084	.1598*	.1418*
	(.0120)	(.0177)	(.0942)	(.0811)
$post_t rend_1 n$.0178	0187	.3532 ***	.3389**
post mand-m	(.0137)	(.0202)	(.1590)	(.1385)
postfrena2n	(.0144)	(.0169)	(.1717)	(.1479)
AGC index=1	()	.0000	()	.0000
AGC index=2		0055		0363
AGC index=3		.0407		.0157
$AGCxPre_t rend1 = 0$		(.1092) .0000		(.1080) .0000
$AGCxPre_t rend1 = 1$		(.) .0000		(.) .0000
$AGCxPre_trend1 = 2$		(.) .0157		(.) .0268
$AGCxPre_trend1 = 3$		(.0195) .0046		(.0228) .0120
$AGCxPre_rend2 = 0$		(.0358)		(.0363)
$100 \times 10t = 0$		(.)		(.)
$AGCxPre_t rend2 = 1$.0000 (.)		.0000 (.)
$AGCxPre_trend2 = 2$.0176 (.0154)		.0220
$AGCxPre_trend2 = 3$		0073		0063
AGCxDisaster=0		.0000		.0000
AGCxDisaster=1		.0000		.0000
AGCxDisaster=2		.0117		.0193
AGCxDisaster=3		(.0169) .0360		(.0183) .0399
$AGCxPost_trend1 = 0$		(.0409) .0000		(.0406) .0000
$AGCxPost_rend1 = 1$		(.) .0000		(.) .0000
$AGCxPost_rend1 = 2$		(.) 0195		(.) 0515**
ACCrePort = ard 1 = 2		(.0192)		(.0224)
$AGCxPost_trena1 = 3$		(.0367)		(.0397)
$AGCxPost_t rend2 = 0$.0000		.0000 _(.)
$AGCxPost_t rend2 = 1$.0000 (.)		.0000 (.)
$AGCxPost_t rend2 = 2$.0244 (.0168)		.0597 ^{***} (.0224)
$AGCxPost_t rend2 = 3$		$.1209^{**}$		$.1396^{**}$
Share of immigrant living in North		()	.1117	.1903
$\mathrm{northxPre}_t rend1$			2363	2812*
$\mathrm{northxPre}_t rend2$			(.1014) 1300	(.1621)
North*Disaster			(.1180) 2353*	(.1117) 2430*
$northxPost_trend1$			(.1365) 5237**	(.1261) 5936 ^{***}
northxPost _t rend2			(.2323) 5804**	(.2235) 6524***
Constant	8550***	8480***	(.2504) 7712***	(.2458) 7387***
Constant	(.0196)	(.0443)	(.2477)	(.2267)
Montnx Year [*]	Yes	Yes	Yes	Yes
No. of countries	10092	81	81	81
Overall-B ²	01/13	0622	0957	1511
_ 2	1500	10022	.0307	.1011

Table 2.18: Efficient specification controlling for other shocks and economic conditions

Chapter 3

Export bans, prices and acreage allocation

Abstract

In this study I evaluate the effect of a series of trade restrictions on maize in the form of export bans imposed by the Malawian government between 2005 and 2017 aimed at ensuring food security and stabilising domestic prices. Addressing the potential endogeneity of export bans by using monthly rainfall and global maize prices as instruments, I do not find strong evidence that on aggregate the restrictions were able to lower domestic prices. Instead, I find that the policies were only able to lower the volatility of maize prices during these periods. Distinguishing the bans based on the factors inducing its imposition, I categorised these bans into demand induced and supply induced export bans depending on whether or not the factors are related to domestic output or external demand forces. I find the policy to be ineffective in the event that the ban is induced by an external demand shock. On the contrary, the policy lead to a fall in domestic prices if the ban is induced by an internal supply shock. On food security, I find that the market uncertainties generated by the unpredictable nature of these policies leads to a decrease in the acreage share dedicated to maize cultivation in subsequent periods. Our findings therefore highlight that, though these policies may be beneficial in the short term, it may have negative consequences on long term food security.

3.1 Introduction

In Malawi, security in maize consumption is synonymous to food security (Stevens and Madani (2016)). Maize is the most widely cultivated and consumed crop in Malawi and contributes significantly in the daily calorie intake of Malawians. As a result, significant attention is paid to it by the government of the day to leverage political support (Ellis and Manda (2012)). Restrictions in the form of export taxes, export quotas and the extreme case of an export ban have been applied by various government including the government of Malawi and other major grain exporters such as Ukraine, Argentina, China, and India among others on basic staple commodities such as cereals (Sharma (2011))¹. These policies have been mostly imposed by governments in response to either a harvest failure or during periods of rising global food prices as was the case in 2008-2009 and in 2010-2011. Between 2007 and 2011, Sharma (2011) identified about 87 such restrictions in about 33 countries spread across the globe mostly by major grain exporters.

While these policies may seem like a thing of the past, the Covid-19 crises have reignited the debate about the reason for the adoption of such policies and their effectiveness (Dawe (2020)). In the wake of the Covid-19 crises, some major crop exporters adopted moves to restrict exports in-light of the uncertainties in agricultural production and disruptions in supply chains generated by the lock-downs instituted in response to the spread of the virus. Starting with personal protective equipment's, some major exporters quickly considered restricting the export of basic commodities. For instance, Vietnam in the beginning of March 2020 stopped issuing new licenses to rice exporters before imposing an export quota on rice in the month of April. Similarly, Cambodia and Myanmar in April of 2020, placed a ban on export of paddy-rice and stopped the issuance of rice export licences respectively (Dawe (2020)). The aim of both the earlier and most recent policies have been mainly to ensure food security and stabilise domestic food prices.

As expected, these policies have generated a literature aimed at evaluating its effectiveness. Diao and Kennedy (2016), Groom and Tak (2015) and Fuje and Pullabhotla (2020) among others have documented the success of these policies in countries such as Tanzania, India and Malawi in averting a spike in food prices during the periods the policies were in place. For instance, Diao and Kennedy (2016), estimate that the export ban lowered producer price of maize farmers in Tanzania by 7 to 25 percent, while Aragie et al. (2018) using a Static General Equilibrium (STAGE) model for Malawi, estimate that in the short run domestic maize prices and grain milling prices decrease by about 15.5 and 13.0 percent respectively. Others on the other hand find mixed results (Aragie et al. (2018)), while some even find contrasting evidence in the ability of such policies to stabilise prices (see Garcia-Lembergman et al. (2017)).

The effect of such policies on price is likely to have significant welfare implications for both

¹Export quota by Ukraine, export taxes by Argentina and China, and export ban by India

consumers and producers especially for small rural farm holders. From a theoretical perspective, Deaton (1989), highlights that the net welfare implication of such restrictions is ambiguous for agricultural households and is dependent on the households net supply and consumption of the good. However, the empirical evidence is mixed. For instance, while Groom and Tak (2015) finds that the Indian governments ban on rice export at the time of the world food crises to have had a net positive effect on the Indian population most of whom are net consumers of rice (about 87 percent). Ha et al. (2015) on the other hand when simulating the impact of Vietnam's rice export policy finds that a free trade policy will yield a more beneficial impact to both Vietnamese households and for global rice markets.

While in many countries such policies are only a one time policy that last for only a short period, in other countries like Tanzania, Zambia, Malawi among others these policies are quite recurring albeit in an unpredictable manner. Despite the series of studies aimed at evaluating the effectiveness of these policies, little or no attention has been paid to understand how the effect of the policy may differ depending on the factors inducing its imposition. Economic theory predicts that demand and supply shocks may have different implications on prices and welfare. However, a distinction of the effect of the ban based on the factors motivating the imposition of the ban is yet to be seen in the literature, despite the fact that the effectiveness of the ban may be dependent on the factors motivating the ban. For instance, a ban on export imposed during periods when domestic output is below domestic demand will probably mitigate but not completely prevent a rise in price as compared to when domestic production is sufficient or above the domestic demand in which case prices may likely fall. On the other hand, if an export ban is imposed in a period of rising global prices, the ability of the policy to shield domestic consumers from higher world prices will depend on the effective implementation of the policy and producers and traders behaviour in response to the ban. In this study, I attempt to fill this gap in the literature by providing a framework that helps to understand the potential implications depending on whether the ban was internally or externally motivated and then make such distinctions in evaluating the effect of Malawi's export ban on prices.

Beyond the role of these policies in price stabilisation and its welfare implications, it is difficult to assess its effectiveness in ensuring food security especially in the long term. This is because the consequence of the ban may extend beyond the period of the ban itself. I argue in this paper that the unpredictability of the policy may induce market uncertainty through increase in price volatility and the potential disruption of supply chains which may have implications on small holder farmers farming decisions and stakeholders investment decision in agriculture in the long-run. The increase in uncertainty may lead to a diversion of resources from the food crop in question in favour of other more profitable crops which are unaffected by the ban. Therefore, another contribution of this study is to use the export bans as a source of uncertainty and asses its effect on maize cultivation. Indeed the role of output price risk have been shown from a theoretical perspective (see Sandmo (1971) and Finkelshtain and Chalfant (1991)) to affect producers production decision depending on their risk preference. Though a recent test of this theoretical predictions by Bellemare et al. (2020) do not find compelling evidence to support this theory. A more extended analysis that study output price risk in the presence of yield uncertainty finds both risk and wealth effects to be important determinants of the corn and soybean acreage decisions of U.S farmers (Chavas and Holt (1990a)). Therefore, the long-run effects of such restrictions is dependent on the supply responsiveness of the producers (Mitra and Josling (2009)).

In this study, I attempt to investigate the effect of a series of trade restrictions on maize imposed by the Malawian government on the relative price of maize in the various markets in Malawi and its price volatility. Unlike previous studies, my approach in this paper is to adopt a Difference-in-Differences strategy that seeks to compare the changes in price of maize relative to changes in price of other crops in the same market during the same period both before and after the policy is implemented². To carry out these analyses, I rely on monthly price data from the Malawian ministry of Agriculture for the major crops traded on the various markets (between 28 to 72 markets) in Malawi between 1990 and 2016. I find that on aggregate the policy is associated with a higher relative price of maize and an increase in price volatility. However, I find that in periods in which there is a higher yield if an export ban is in place, maize prices are relatively lower. Separating the ban into demand induced and supply induced based on the factors generating the ban, I find that maize prices are associated with higher prices for an externally induced export ban (demand shock) than an internally induced export ban (output or supply shock).

Noting that the imposition of an export ban is not random, and hence any estimates that does not account for this may not uncover the causal effect of the ban, I adopt the following approach. First, I restrict my sample to only maize and use an instrumental variable approach to to solve the issue of the non-randomness in the policy. I specifically use monthly rainfall, global maize prices and their interaction with previous years yield to instrument the ban. Without instrumenting the ban, I find results similar to that of the full sample. Once I instrument the export ban, I find that the ban is ineffective in preventing a rise in maize prices. However, it is able to reduce the volatility in maize prices. Once I distinguish the ban based on the factors motivating it, I find robust evidence that these policies are ineffective in preventing a rise in maize prices if the ban is induced by an external demand shock, whilst on the contrary, the ban significantly reduces domestic maize prices if the ban is imposed in response to a supply shock. The reason for this perhaps unexpected results lies greatly in the effective implementation of

²This is motivated by the believe that the relative change in price of a commodity within a given market is of much more concern to both producers and consumers than a change in the absolute price of a crop or a change in the price of a crop relative to the price in other markets or neighbouring countries, see Porteous (2017) and Fuje and Pullabhotla (2020). Though from a policy perspective, a comparison of a change in domestic prices relative to international prices is likely to be the object of interest.

the policy and the trading response of traders.

In the second part of the paper, to investigate the effect of the ban on food security, we focus on how farmers relative aggregate acreage share dedicated to maize cultivation at district level responds to the ban. I rely on data from the Malawian Ministry of Agriculture, Irrigation and Water development for the aggregate monthly price data of the major crops traded on each market as well the annual land cultivated and quantity harvested in each of the the main districts in Malawi. Using the two-step GMM estimator by Arellano and Bover (1995), I find that the uncertainties generated by the export bans lead to a decrease in the share of land allocated to maize cultivation and increases the share of land allocated to the cultivation of other crops. A higher overall price of other crops and or a higher yield in the previous year reduces the acreage share allocated to maize production. On the contrary, a higher price of maize in the previous year increases the acreage share of maize in the subsequent farming season.

The study is organised as follows; in the next section, I provide the background context of my study, in section three, I provide a brief review of the literature, in section four, I present the theoretical framework of my analyses, in section five, I describe the methodological approach used in the study, the results are present in section six and in section seven the conclusions and potential implications of my findings are discussed.

3.2 Background

In Malawi like in many other developing countries, agriculture has been and continues to be the dominant sector of its economy. The sector contributes about 30 percent to the country's GDP and accounts for over 80 percent of the country's export revenue. The sector serves as a source of livelihood for over 80 percent of its population and employs about 64 percent of its labour force (World bank 2018). Therefore any policies that may affect the prices, production decision and or trade could have significant implications on the welfare of households such as on poverty, inequality and food security especially for the vulnerable rural population.

Maize production and consumption in Malawi

Maize is the main staple crop in Malawi providing for over 65 percent of the daily calorie intakes of Malawians. Hence maize production is synonymous to food security in Malawi (Stevens and Madani (2016)). Maize production is mainly dominated by a large number of small scale farmers and a few large scale farmers. It is cultivated by more than 90 percent of agricultural households who mostly live in rural areas accounting for about 60 percent of all cultivated agricultural land Stevens and Madani (2016). The local maize variety is the main maize variety cultivated. However, the availability of higher yielding maize varieties such as





the hybrid and compost maize have also gain traction among the local farmers in recent years, thanks to a government subsidy program implemented since 2005 Dorward and Chirwa (2011). Most farmers despite growing maize are net consumers of the crop. About 60 percent of all maize produced is consumed by cultivating households themselves, only about 14 percent of rural households and 3.5 percent of urban households are sellers of maize (IHS 2010/2011). The growing season in Malawi starts from October and goes through April while the harvest season starts in April and all through June depending on the planting date and weather conditions. Low rainfall, dry spells or extremely high temperatures in the early part of the planting season is especially harmful for maize production³. Maize production and maize available for domestic food supply has been increasing over the years inline with increasing population, albeit with strong volatility in output mainly due to volatile weather conditions as can be seen from figure [3.1]. Total Maize production increased from a little over one million metric tonnes in the 1970's to over two million metric tonnes in the early 2000's and recently to over three million metric tonnes to meet increasing demand.

Its trade is dominated by government agents who mostly buy it for storage in government facilities, large scale buyers who mainly engage in the export trade, and small traders who resell it in the local markets (Ellis and Manda (2012)). Farmers also have the option to sell their output themselves directly in the local market to fetch higher prices. Some of the maize produce is exported mainly to neighbouring east African countries. However, maize exports are quite low. For instance, between 2009 and 2011 only about 5 percent of all maize was formally exported. The government mainly relies on imports to supplement the fall in domestic production to meet increasing domestic demand as can be seen from figure [3.2]. For instance, in the 1990's government heavily relied on imports to make-up for the series of harvest failures that occurred during this period. Maize accounts for about 28 percent of agricultural GDP.

³See Lobell et al. (2011) for empirical evidence on the impact of extreme temperatures on maize yield.

Trade policies

The government of Malawi beginning in the 2000's have intermittently imposed various trade restrictions mostly in the form of export bans on maize. These policies are mainly imposed in response to harvest failures or expectation about it, thereof. The foundations for such trade restrictions can be traced back to the governments enacting of the control of goods act (1968) which was designed primarily to protect indigenous enterprises.

The trade policies are mostly preceded by the government accusing traders of hoarding maize stocks, government interfering in the market and setting ceiling prices and promising to import large stocks of maize from neighbouring countries all with the aim of provoking traders to release their excess stocks to the market. This is then followed by trade restriction both internally and externally (Ellis and Manda (2012)). The extreme case of an export ban has been the governments ultimate last resort. The first ban considered in this study was imposed from July 2005 to Feb 2007 and a second one imposed from April 2008 to August 2009 and more recently a long term ban that started from December 2011 to October 2017⁴

Like in many other countries, the aim of these policies has been to ensure food security and stabilise prices. However, the conditions that trigger such policies most often is a combination of factors. For the case of Malawi, the reason for the imposition of an export ban has varied; in 2005 and in 2011, the export ban was mainly imposed due to a local harvest failure and dwindling stock of maize reserves resulting from a drought in the preceding year⁵ while that of 2009-2011 was purely motivated by the desire to shield its populace from rising international prices. The case for the long term ban from 2012 to 2017 was more of a concern for food security as a result of series of weather shocks. In essence, though the policies have a similar objective, they are driven by different motivations; the former is supply driven and the latter is demand driven. Therefore, we may expect the same policy to have different implication with regards to the extent at which it is able to stabilise prices and its consequent welfare effect.

Export bans and disasters

Analysing disaster data from the EM-DAT database to corroborate the reasons for the source of the restrictions, I find that Malawi is quite prone to weather shocks. Malawi suffered from several floods between 2001 and 2002 that affected over 500,000 people and a drought that caused famine for over 2.8 million people. Though during this period an outright export ban was not imposed, a ban on private maize trading was put in place in January 2002. A similar ban on private maize trading was also imposed in January 2006 and in August 2009 on top of existing export bans. A maximum buying price was also imposed in May 2008 requiring all

⁴However, it has been noted that despite the export bans, some quantities of maize were still exported. For instance, during the first ban between July 2005 to January 2007, about 71,000 mt of maize were exported through formal channels whilst about 2,500 mt per month was exported informally between December 2011 to February 2013 (Edelman and Baulch (2016)).

⁵However, despite a similar harvest failure in 2001/2002 planting season, no export ban was imposed.

maize purchasers to obtain a licence and report their transactions regularly (Ellis and Manda (2012)).

Beginning October 2005, the southern and central region of Malawi was hit by a drought which caused food shortage that affected an estimated 5 million people, while at the same time the northern region of the country was hit by severe floods which affected over fortyfour thousand people. Subsequent flash floods were recorded both in 2006 and 2007 affecting an estimated seven hundred thousand people. This provides strong suggestive evidence that domestic factors played an important role for the export ban imposed between 2005 and 2007.

Series of floods were recorded in various part of the country between 2008 and 2011. However, these events affected a relatively smaller number of people (on average about twenty thousand) compared to those that occurred in 2005. This suggest that the export bans imposed between 2009 and 2011 were unlikely to be motivated by domestic factors, rather external factors such as rising global food prices would have been a major motivating factor.

The period between 2012 and 2017 was characterised by a series of floods and droughts spread across the country with floods being more widespread in the southern an central region of the country. A drought than began in 2012 all through 2013 mainly in the south and centre of the country caused food shortage for an estimated 1.9 million people and the drought that began in October 2015 and lasted through 2017 affected an estimated 6.7 million people. This also reveals that Malawi's long term export ban was to a large extent motivated by internal factors.

3.3 Literature Review

Effect of export bans and other non-tariff barriers on prices

The first objective of this study is to examine the effect of the export ban on the relative price of maize received by small holder farmers in Malawi. One would expect that an export ban would affect prices in the domestic economy only if the policy is binding, i.e if in the absence of the policy, a positive quantity of the commodity would have been exported. I begin this section by first providing a conceptual framework of the conditions under which an export ban may affect domestic prices and the extent to which they may be affected drawing insights from the previous theoretical literature and then summarise the existing empirical evidence.

Conceptual framework

Export ban refers to an outright prohibition on the export of a good outside a country, similar to placing a zero export quota on a good (Mitra and Josling (2009)). The reasons leading to the imposition of such restrictions can be generally grouped into two namely; internal and external factors. Internal factors mainly refer to those arising as a result of a fall in domestic production

due to bad weather conditions such as drought or rainfall that destroys crop and thereby posing a threat to food security. External factors on the hand refer to events happening in neighbouring countries and the global markets such as crop failure in major crop exporting countries or an increase in demand for bio-fuel leading to rising global food prices that makes export very lucrative thus driving up local prices. In this section I attempt to provide a framework to help analyse the implication of export bans distinguishing between those generated by internal factors and those generated by external factors.

General effect of an export ban

Mitra and Josling (2009) provide an analytical framework to understand the effect of an export ban. They propose a framework that is more aligned with externally generated ban. They note that an export ban have a re-distributive welfare effect in favour of consumers, through the distortionary price effect generated by the ban. Thus leading to an aggregate welfare loss in the absence of market imperfections. The increase in the quantity of the commodity supplied in the domestic market as a result of the ban suppresses domestic prices. In the short-run, the extent to which prices are distorted and the aggregate welfare gain or loss rests mainly on the price elasticity of the commodity. For commodities for which the demand is highly responsive to a price change, only a small drop in price will be required to absorb the excess quantity. This means that if a ban is placed on a commodity whose demand is inelastic, a larger drop in price will be required to absorb the excess quantity. Therefore a ban will result in a greater welfare loss for a commodity whose demand is inelastic relative to commodities faced with an elastic demand. This is mainly because in the short-run producers have limited space to mitigate the effect of the lower prices and are therefore forced to sell their produce at the existing market prices. However, in the long-run the aggregate welfare effect of the ban depends on the behavioural response of the producers to the fall in price as we would see in the next section.

Export ban in presence of output shock

The analysis of export ban described above best depicts the situation when the export ban is imposed out of concerns that the favourable international prices may lead to excess export of the good in question and thus driving domestic prices upward. It essentially assumes that ban is motivated by external factors and that domestic production and consumption were initially unaffected (in equilibrium) and that the subsequent change in price and quantity traded is purely in response to the ban. While this is one of the possible scenario's of an export ban, another scenario which is most often observed is when an export ban is imposed in response to a decline in domestic production (say harvest failure) as a result of flooding, drought locust invasion and or other related factors. Assuming the market is initially in equilibrium, a harvest failure reduces the quantity of the crop supplied in the market thus raising domestic prices in the absence of any government intervention. The extent of the rise in price and its welfare implications will depend on the demand elasticity of the good and if it is open economy the quantity of the goods imported. If the government response to the shortage in domestic production by imposing an export ban on the crop, this will increase the quantity of the good available in the domestic market and possibly mitigate the rise in price previously induced by the fall in supply, the extent to which price falls will depend on the share of the good previously exported. Three scenario's are possible;

i) The quantity exported is equal to the deficit in domestic supply caused by the harvest failure. In this case, a ban on export restores the domestic price to its initial equilibrium level.

ii) The quantity exported is greater than the fall in domestic production, in this case prices will fall below its pre-crises level.

iii) The quantity exported is less than the fall in domestic production. In this case, the export ban though will mitigate the effect of the harvest failure, prices will still rise.

Of course the above analysis depends on some fundamental assumptions; such as the absence of storage facilities, the degree of elasticity of demand of the good, the effectiveness of the ban on restricting exports etc. Using this framework, we can clearly infer on what is the expected effect of a ban on maize export on maize prices in Malawi once we know the conditions leading to the imposition of a ban.

Existing empirical evidence

Most of the studies in the literature are aimed at investigating the effectiveness of the policy in lowering domestic prices. However, the evidence so far is mixed. Diao and Kennedy (2016), studied the impact of Tanzania's export ban on maize using a Computable General Equilibrium (CGE) model and Tanzania's social accounting matrix for 2009. They estimate that an export ban lowers Tanzania's food price index between 0.6 and 2.4 percent highlighting the low contribution of maize to overall food price inflation. In terms of maize prices, their estimates reveal a differential impact of the policy depending on the region ranging between 7 to 26 percent. Taking into account the varying geographical characteristics of the domestic markets, 10000 (2015) instead analyse the impact of the ban within the different regions in Tanzania depending on their level of integration within the East African community. They use data from the Tanzania household budget survey 2007, ministry of industry and trade and the Food and Agriculture organisation. Their findings reveal that regions bordering with the EAC have higher transmission rates of international prices to domestic markets compared to those further away from the EA borders. Similar to Diao and Kennedy (2016), they find the ban to have a had a differential effect in the different regions within the country, an increase in price for EAC border regions and a decrease in prices for regions further away from the border.

Using a Static General Equilibrium (STAGE) model calibrated to the 2010 Social Accounting Matrix (SAM) for Malawi, Aragie et al. (2018) simulated the effect of an export ban on Maize and a proposed Oil seed export levy. In the short run, they estimate a 15.5 and 13.0 percent decrease in domestic maize prices and grain milling prices respectively with a consequent effect on disposable income. They estimate about a 0.1 percent and 2.4 percent decline in small scale and medium scale rural farm household income respectively while non-farm households income rise by about 2,4 percent. The decreased in prices was accompanied by an increase in maize consumption for both rural and urban households with the latter experiencing a disproportionately larger increase. In the long-run however, the effect is muted by farmers behavioural response to the policy. For instance, the decrease in maize price is relatively lower, about 3.3 percent as a result of the supply response of farmers who decrease maize production by 6.6 percent. This findings suggests that the policies may have the intended effect in the short-run which may explain why these policies seems appealing for politicians, however, it may have a distortionary effect in the long-run.

Taking into account the total quantity harvested and seasonality in prices, Fuje and Pullabhotla (2020) use monthly maize price panel data on 152 markets in Malawi and its neighbouring countries of Tanzania and Zambia to asses the short term effect of Malawi's export ban on maize. They used the price-dispersion between two similarly distanced markets, one in Malawi and another in a neighbouring country to identify the impact of the ban on prices and used Deaton (1989) statistical welfare analysis framework of compensating variation to assess the welfare implications of the policy on households welfare. In their analysis they control for the quantity of the harvest, seasonality of prices and the existence of trade restrictions in neighbouring countries. They find the bans to be associated with decrease in domestic prices, a lower relative price of about 6.8 percent and less seasonality in maize prices in Malawi.

A more general study by Porteous (2017) which use monthly market-level price data from 49 large markets in 12 countries in East and southern Africa out of which five countries imposed altogether 13 distinct bans on maize export which is the staple crop in the region. He investigates the effect of the ban on gaps in maize prices between pairs of cross-border markets and finds that export bans in the region did not have any effect on price gaps between the country imposing the ban and their trading partners. This results are robust to analysing the bans jointly or separately. In essence he finds the policies to be unsuccessful in achieving their intended objectives. He instead finds that they have the opposite effect of leading to higher and more volatile prices in the counties imposing the ban.

Price uncertainty and farmers behaviour

The Ad-hoc and unpredictable nature of the export ban policy imposed by the Malawian government aside from denying farmers access to higher prices for their produce also induces uncertainty and generates volatility in output prices. In countries like Tanzania, these policies had the effect of discouraging the scrupulous nature of traders who will buy farmers produce upfront before the harvest at very low prices especially from financially constrained farmers denying them the potential higher prices from exports Kagira (2011). This though may eliminate this activities of traders, it could also lead to lower investments.

Theoretical background

An essential component of a literature in agricultural economics devoted in studying farmers production decisions in developing countries has been to understand the role of output price risk on farmers production decisions. This literature has mainly drawn insights from the literature on firms behaviour under risk. The seminal paper by Sandmo (1971) established that in the presence of price uncertainty, the firms optimal output is much smaller than the competitive output under certainty and that risk averse firms will produce lower output than risk-neutral firms in the presence of output price risk. Sandmo (1971) and many other studies that followed use the expected utility hypothesis and assume that utility depends only on the random variableprofits, ignoring other risk factors that may affect utility levels. Consistent with this predictions, many policy instruments are based on the notion that farmers dislike output price risk and that they hedge against this risk by producing relatively lower output in situations of price uncertainty.

Finkelshtain and Chalfant (1991) extended Sandmo's model of the firm to study peasant agricultural households by combining it with the literature that study the marketing of surplus output, using alternative notions of risk aversion. Noting that agricultural households are sometimes characterised by also being a consumer of its own produce exposes the peasant farmer to multiple risks because now not only is the price of its output random but also a price of its consumption good ⁶. This interaction within households between production and consumption decisions sets agricultural households distinct from other forms of producers. Hence suggesting that these two risk cannot be modelled in isolation. Consequently, risk averse farmers may not produce an output below its profit maximising level when faced with price uncertainty.

Existing evidence shows that price volatility induces output price risk which have negative implications on the resource allocation and investment decisions of producers (Sandmo (1971), Moschini and Hennessy (2001)). This is especially a problem for small farm holder agricultural producers who have little or no insurance for their agricultural produce, being buyers and

 $^{^{6}}$ One of the main distinction between Sandmo (1971) and Finkelshtain and Chalfant (1991) is that, the former is only a producer of the good whilst in the latter the peasant farmer could be both a producer and a consumer of the same good

consumers of the commodity at the same time (Finkelshtain and Chalfant (1991)) reinforces this problem.

One of the most important determinants of food supply in the short-run is the acreage allocation decision of producers. While prices or output maybe stochastically influenced by weather, pest attacks etc; they mostly occur in the post planting period and as such the agricultural economics literature on crop production decisions favours estimating acreage response over output response (Coyle (1993)). Focusing on acreage area allocation is the most important decision variable available to farmers in the short-term, since a change in productivity mostly as a result of technological progress only happens over a long period (Roberts and Schlenker (2009)).

Existing empirical evidence

Bellemare et al. (2020) provide an empirical test of Sandmo's theoretical predictions on the theory of producer behaviour in the presence of output price uncertainty by conducting a lab in the field experiment with US college students and Peruvian farmers. They use a two stage randomise design to assign individuals to either the certain or risky output price group and then conditional on being in the risky price group, subjects are further randomly assign different levels of risk. This allows them to both investigate the intensive and extensive margin of the output price risk. Their study did not find any significant change in output in response to a price risk at the extensive margin, the only exception being when individuals are risk neutral which is inconsistent with the vast majority of producers who are risk averse in nature. However, they do find a decrease in output produced at the intensive margin once a linear relationship is imposed between the two. The decrease in output at the intensive margin is consistent with Batra and Ullah (1974), though this result is only valid for the sample of college students in the US and not for Peruvian farmers.

An extension on the analysis of producer behaviour in response to risk is proposed by Maples et al. (2013) who introduced input price uncertainty in addition to output price risk in a theoretic framework. They then tested their predictions using data on cattle producers in the US and find that producers increase their use of input when faced with input price uncertainty and lower their output.

Chavas and Holt (1990a) developed a theoretic framework that model the decision of acreage supply response under uncertainty using the expected utility maximisation. They developed a household decision model that incorporates both output price and yield uncertainty and used it to empirically estimate the behavioural relationship of risk-responsiveness of acreage to corn and Soybean prices in the US while accounting for government price support programs and initial wealth of producers. Their findings reveal both risk and wealth effects to be important determinants of the acreage decision. Garcia-Lembergman et al. (2017) estimates the effect of a quantitative export restrictions imposed on cattle beef by the Bolivian government. Using country-level panel data that spans between 1961 and 2013, the authors used a synthetic control approach to evaluate the impact of the policy. They found the restrictions to have decreased total production by about 42 percent and furthermore also decreased production for the domestic market by 56 percent. They argued that this reduction in domestic supply might have been the driver of the increase in the price of cattle beef observed during this period. Their findings are consistent with a distortionary effect on quantity.

3.4 Data

To investigate the effect of the ban on relative maize prices and its volatility, I use monthly price data from the various market in Malawi that numbered between 27 and 74 obtained from the Ministry of Agriculture, Irrigation and Water Development of Malawi covering the period 1990 to 2018⁷. The data provides monthly prices of major crops traded in each market over this period. The number of markets for which data is available have been steadily rising from 27 markets in 1990 to about 74 markets in 2006. The price data is mostly collected on a weekly basis and its weekly values averaged to obtain the monthly estimates at market level and national level. Malawi does not collect data on wholesale prices rather the retail prices are what is reported. However, the difference between these two prices are negligible, for instance, retail maize prices represent about 97 percent of its wholesale price.

Data on Malawi's food balance is obtained from the Food and Agriculture Organisation (FAO) website. It provides annual data from 1961 to date about total production, total domestic supply, total quantity of a crop available for food supply, exports, imports, change in stock and other uses of crop. These data are used to understand the evolution of the crop overtime.

To investigate the effect of the ban on small holder farmers, I rely on annual production data; area cultivated, output harvested and average annual prices from the Malawi's ministry of agriculture and the FAO website. The data are available at eight aggregate district levels over the period 1998 to 2019. Monthly global corn price data is obtained from the Federal Reserve Bank of St. Louis website⁸. Monthly rainfall data is obtained from the World bank climate change knowledge portal⁹. Disaster data partly used to categorise a ban as either demand induced or supply induced through the number of people affected by a given disaster is obtained from the EM-DAT cred database¹⁰.

⁷I thank Rosemary, a research analyst at IFPRI and Jennifer Nkosi an Economist at the Department of Planning in the Ministry of Agriculture in Malawi for making this data accessible to me.

⁸https://fred.stlouisfed.org/series/PMAIZMTUSDM

 $^{^9 {\}tt https://climateknowledgeportal.worldbank.org/country/malawi/climate-data-historical}$

¹⁰https://www.emdat.be/

3.4.1 Summary statistics

Figure [3.3] show the evolution of maize prices between 1998 and 2018. The areas shaded in grey refers to the period during which an export ban is in place. We note a high level of variability in monthly prices, prices being low in the peak harvest season and high in the lean season. The table below presents the average monthly prices on the various markets for each crop. We see on average maize have a relatively lower price compared to most of the other crops, is cultivated on a larger acre of land and has a higher share of land in each district dedicated to its cultivation.

From the descriptive statistics presented below, we can observe a positive relationship between a poor harvest in the previous period and a ban being imposed in the subsequent period as is the case for the maize ban imposed in the mid of 2005. Also we observe a negative relationship between prices and total production.

In terms of acreage, we observe that the share of land allocated to maize production to be declining since the aftermath of the first maize export ban that was imposed in 2005.



Figure 3.3: Average real monthly maize prices

This data is obtained from the FAO food balance sheet data for Malawi.

3.5 Methodology

3.5.1 Empirical framework

The goal of my empirical framework is to identify the effect of Malawi's export ban on relative maize prices and its volatility as well as its effect on aggregate acreage share allocated to maize cultivation. To identify the effect of the policy, the analysis requires controlling for any systematic shocks to maize that are correlated with, but not due to the ban. I do so by including a host of fixed effects and also using other crops to serve as controls against which the changes overtime are compared. Later, I restrict the sample only to maize crop and use rainfall and its interaction with previous years yield to instrument the ban.

To evaluate the effects of the export ban on small farm holders cropping decisions in Malawi, this study adopts a two step approach. First, using monthly price data from the various markets in Malawi, I investigate whether the export ban had any effect on relative maize prices and its volatility. In the second stage, I use aggregate annual data to investigate how farmers maize cultivation decision has been affected by the ban. I use other major crops grown in Malawi for which comparable data is available as my control crops. These crops are rice, cassava, beans, groundnuts, pigeon pea, cow pea, finger millet and bulrush millet as my control crops. These crops play a non-negligible role in both production and consumption baskets of households. For

Table 3.1: Summary statistics

crop	price	Sd price	lProduction	lyield	share
BEANS GENERAL	5.14	0.25	8.87	-0.38	3.37
BULRUSH MILLET	4.53	0.34	5.90	-0.82	0.99
CASSAVA ROOT	3.72	0.32	12.79	2.89	7.99
COW PEAS	4.71	0.30	6.85	-0.76	1.21
DOLICHOS BEANS	4.84	0.19	5.70	-0.60	0.20
FINGER MILLET	4.89	0.31	6.42	-0.37	0.77
GROUND BEANS	4.92	0.25	5.85	-0.56	0.21
MAIZE	3.66	0.19	12.02	0.54	31.87
PIGEON PEAS	4.68	0.23	6.57	-0.37	2.03
RICE POLISHED	5.04	0.16	9.40	0.60	2.63
SHELLED G/NUTS	5.20	0.27	9.37	-0.25	5.13
SORGHUM	4.57	0.30	6.03	-0.31	1.53
SOYA BEANS	4.74	0.30	6.93	-0.40	0.86

Figure 3.4: Evolution of crop prices



The shaded area in gray refers to the periods in which an export ban was in place. The first shaded area corresponding to the first export ban of 2005 and the second and third corresponding to the bans of 2009 and 2012 respectively.

instance, beans are the major source of protein intake for Malawian households, the others are grains similar to maize and could potentially serve as substitutes and with varying degrees of domestic consumption and local consumption.

It is clear from figure 3.5 that in 2005 there was a sharp decline in crop yield for all crops as a result of the harvest failure in that year which was the motivation behind the imposition of the ban. Subsequent disasters did not have a very pronounced effect on crop yield. Similar

Figure 3.5: Evolution of crop yield







trajectories are also observed in terms of crop production.

3.5.2 Empirical model

To investigate if the imposition of an export ban on maize had any effect on relative maize prices, most studies on the effect of export bans compare maize prices relative to prices in neighbouring countries, international prices or relative to periods of no export ban. While this may clearly seem to be the objective of governments when such policies are imposed, i.e. to stabilise domestic prices relative to international prices, consumers instead mostly account for prices in relative terms either with respect to other crops in the domestic market or in respect to some other periods. Therefore, it is imperative to investigate the effect of these policies along these lines. In this paper, we attempt to fill this gap in the literature. I also proceed to investigate the effect of the ban on relevant dimension of the policy, i.e. the effect of the ban on price stability. I use a similar approach as Fuje and Pullabhotla (2020) and estimate the following model

$$P_{i,j,t} = \lambda_{i,j} + \tau_t + \delta_i Ban_t + \beta_i Maize_i * Ban_t + \varepsilon_{i,j,t}$$

$$(3.1)$$

where $P_{i,j,t}$ is the log of real price (Kwacha/kg deflated by the consumer price index for Malawi) of crop i in market j at time t; $\lambda_{i,j}$ is a crop-by-market fixed effect; τ_t is a month-by-year fixed effect; Ban_t an indicator for the export ban in time t and $Maize_i * Ban_t$ is the interaction of the ban with the indicator for the Maize crop. The inclusion of the crop by market fixed effect eliminates the need to include the maize dummy or dummies for the control crops since they will already be captured by the fixed effects. λ_i , τ_i , δ_i and β_i are a set of parameters to be estimated while $\varepsilon_{i,j,t}$ is the error term. One would expect δ_i to be insignificant if the ban is not associated with an overall change in price and if the ban has an overall effect on all prices the sign of the coefficient will depend on the direction of the effect. My key parameter of interest is β_i which captures the association between the ban and the relative price of maize. A negative sign on this coefficient suggest that the ban is associated with lower price of maize relative to other crops and vice-versa. The inclusion of time fixed effects control for any seasonal and national trends in prices of crops and the crop-by-market fixed effects controls for crop-market specific shocks thus allowing us to estimate within market variation for each crop.

Then to examine the extent to which prices might be affected by the quantity harvested, model [3.4] above is extended to control for output yield per acre for each crop¹¹. However, I should mention that this variable is neither available on monthly basis nor for each market

¹¹An alternative might be to use harvest per-capita as in Fuje and Pullabhotla (2020). However, we argue that controlling for yield per hectare is more accurate since it accounts for any difference in area cultivated. Noting that yield may be a function of input usage, controlling for the period during which the fertiliser subsidy program was being implemented and or an index for fertiliser prices, will be useful.

rather it is only available at annual level for only the major districts. Nonetheless, I do not attempt to interpolate it since most crops are harvested only once a year¹². Note that unlike Fuje and Pullabhotla (2020) who use total harvest at national level, I use the total harvest aggregated at major districts instead and normalised it with the total land cultivated in each of the districts rather than the total population. Since trade occurs more frequently between markets in the same region, I argue that prices in closely distant markets are likely to be more responsive to harvest in nearby districts rather than total national harvest.

$$P_{i,j,t} = \lambda_{i,j} + \tau_t + \delta_i Ban_t + \beta_i Maize_i * Ban_t + \phi_i yield_{i,d,t} + \varepsilon_{i,j,t}$$
(3.2)

where demand is a dummy variable equals to one if the ban is induced by external demand shock and zero otherwise. Similarly supply is a dummy equals to one if a ban is induced by a supply shock. It is reasonable to expect an increase in yield to be associated with an increase in harvest which is likely to lead to lower prices and hence we expect $\phi_i < 0$. ϕ_i can be interpreted as the elasticity of price with respect to yield per acre. Finally, to gauge the effect of an increase in yield in the presence of an export ban, I include the triple interaction between the indicator for the maize crop, the ban dummy and the yield variable.

$$P_{i,j,t} = \lambda_{i,j} + \tau_t + \delta_i Ban_t + \beta_i Maize_i * Ban_t + \phi_i yield_{i,d,t} + \gamma_i Maize_i * Ban_t * yield_{i,d,t} + \varepsilon_{i,j,t}$$
(3.3)

This captures the association between prices and an increase in yield when an export ban is in place. An increase in yield when the export ban is in place is expected to make the ban more binding and hence will lower the relative price of maize. In this case we expect $\gamma_i < 0$.

3.5.3 Demand induced vs Supply induced Export ban

We now differentiate the export ban based on whether it is induced by a an external demand shock or an internal supply shock to investigate if there exists a differential effect on prices. This distinction will allow us to asses the effectiveness of the ban depending on the circumstances surrounding the imposition of the ban. We modify models [3.4], [3.2] and [3.3] above by splitting the ban indicator into two variables, demand and supply induced ban indicators as indicated below;

 $\underline{P_{i,j,t} = \lambda_{i,j} + \tau_t + \delta_1 demand_t + \delta_2 supply_t + \beta_1 Maize_i * demand_t + \beta_2 Maize_i * supply_t + \varepsilon_{i,j,t}}_{12}$ (3.4) ¹²An alternative though is to distribute the quantity harvested around the harvest season and see if it makes any difference in the results.
In which of this two scenarios are export bans more effective is not straight forward. Though in principle we might expect the ban to have a larger effect if the ban is induced by external demand forces rather than internal forces. See the appendix for the theoretical predictions of how prices might be affected depending on the origin of the ban. If both demand and supply induced bans have similar effects, then δ_1 and δ_2 should not be statistically different from each other.

3.5.4 Restricted analyses: Maize crop only

Instrumental variable

From the previous sections, we note that both maize cultivation and consumption in Malawi differs markedly with each of the other crops grown and consumed in Malawi. These activities one might expect will be related to maize prices and the imposition of an export ban. Therefore, a simple comparison of the evolution of maize prices and prices of other related crops in Malawi would likely not reflect the effect of the ban, but also the effect of any pre-existing differences in prices and its determinants. Besides, since no other crops are directly comparable, the parallel trend assumption underlying the DID analysis is unlikely to hold. Moreover, one would expect a pure time series analysis of the effect of the maize export ban on maize prices will be contaminated by the series of harvest failures both locally and internationally¹³ especially the events of 2005/2006 and the 2011 harvest failure which in it self triggered the imposition of the ban. As a way of circumventing these issues, I apply the following strategy; instead of directly comparing maize prices with prices of other crops, I restrict my analysis to only maize crop and repeat the analyses conducted earlier¹⁴.

Furthermore, since the imposition of an export ban is not random, any direct comparison of outcomes may not reflect a causal effect of the ban. As such it is important to disentangle the effect of the ban from other factors that may drive the imposition of the ban. The ban is endogenous since it is correlated with other factors contained in the error term¹⁵. I therefore propose to use monthly rainfall, global maize prices and their interaction with previous year's yield as IV's to account for this endogeneity between the error term and our explanatory variables. It is reasonable to expect that rainfall is directly correlated with maize harvest but not correlated with other factors that might affect maize prices sch as domestic demand or international price of maize. Similarly, Malawi exports only a tiny share of total maize exported globally and hence events happening in Malawi are unlikely to affect international maize prices. On the other hand, Malawian traders export decisions are likely to respond strongly to international prices.

 $^{^{13}}$ Harvest failures are likely to have a differential effect on maize relative to other crops

¹⁴In this case comparing within market variation.

 $^{^{15}}$ Note that the ban would be correlated with the error term if for instance (a) we have omitted variables from the model that are correlated with the ban and prices, b) the actual date the ban comes into effect is not known (in other words the ban is measured with error) c) both the ban and prices are simultaneously determined.

3.5.5 Export bans and acreage decision

We illustrate the effect of the export ban on acreage decision using aggregate annual data for major districts in Malawi. I investigate aggregate acreage allocation response to the ban by focusing on the share of acreage dedicated to maize cultivation overtime relative to other crops¹⁶. I follow the approach in the literature controlling for own price and cross-prices as well as the share of land allocated to a crop in the previous period. i_{iii} finds a crops own price in the previous period to be a significant determinant in the acreage allocation decision in the next period. Similarly i_{ii} finds finds prices of related crops to be an important input in the acreage decision making process.The share of land allocated to the cultivation of a crop in the previous period has been used by .. to control for....

following Kim and Moschini (2018), I use the following specification to investigate if the ban had any effect on acreage shares dedicated to maize cultivation;

$$S_{k,d,t} = \gamma S_{k,d,t-1} + \alpha_{d,k} + \tau_t + \delta_i Ban_t + \beta_i Maize_i * Ban_t + \phi_i Price_{k,t} + \theta_i Yield_{k,d,t} + \epsilon_{k,d,t}$$
(3.5)

where $S_{k,d,t}$ is the share of acreage dedicated o the cultivation of crop k in district d at time t; $\alpha_{d,k}$ are a set of district by crop fixed effects; Ban_t and $Maize_i * Ban_t$ are same as before; $Price_{k,t}$ are previous months prices used as a proxy for the expected future price of crop k at time t, i.e. during the planting season and $yield_{k,d,t-1}$ is last years yield used as a proxy for the expected yield.

It is well known in the econometric literature that estimating model [3.5], a dynamic panel data model with ordinary least squares (OLS) yields an inconsistent and biased estimate due to the correlation of the lagged dependent variable with the error term (Nickell (1981)). This is because both the current and lagged acreage share are functions of the fixed effects ($\alpha_{k,d}$) which violates the strict exogeneity assumption. Using the fixed-effect estimator also known as the within-group transformation does not solve the problem either since the lagged dependent variable still remains correlated with the error term. According to Roodman (2009) the bias resulting from estimating such a model with simple OLS is positive (upward bias) while the bias resulting from using a fixed effect estimator is negative (downward bias)¹⁷. The estimate of the true parameter lies in between the OLS and FE estimate for the lagged dependent variable. We therefore estimate model [3.5] using the Arellano and Bover (1995) two-step system GMM estimator (Roodman (2009)) to account for the persistence in acreage shares and the endogeneity of the export ban. The model is estimated using annual data at aggregate district level from 1998 to 2019 for 13 major crops

¹⁶Aggregate response is consistent with the choices of a representative farmer who aims to maximise utility or profit.
¹⁷The direction of the bias is mainly determined by the correlation between the lagged dependent variable

¹⁷The direction of the bias is mainly determined by the correlation between the lagged dependent variable and the error term.

3.6 Results

Export ban and relative maize price

I start my analyses by simply comparing the prices of maize relative to other crops in periods with and without an export ban. Simply estimating the models in equation [3.4], [3.2] and [3.3] above, I find a positive relationship between the export ban and overall crop prices that is significant at conventional significance levels. My estimates show that on average overall crop prices are about 10% higher in the period during which an export ban is in place. This is not a likely unexpected outcome since these bans are imposed in most cases in response to some systematic shocks that affect overall total output. During the periods of an export ban, maize prices are much higher relative to other crops, about 23 percent higher (see column 1 and 2 of table [3.2]). The reason for the higher effect on maize is due to the disproportionately important role maize plays in both the production and consumption basket of Malawian households. However, we note that this initial estimates can be seen as the effect of some underlying factors that induce the imposition of the ban rather than the effect of the ban itself. One could imagine this for instance to mean the effect of a harvest failure on crop prices. To understand the effect of the ban on maize prices, one needs to be able to isolate the effect of the harvest failure on prices from the effect of the ban.

Since we note that quantity of output harvested is an important determinant of output price, I control for yield per hectare by district which is available annually. Not surprisingly, I find an increase in yield to have a negative relationship with price. Further interacting yield per hectare with the double interaction between maize and the export ban indicator, I find an increase in yield when an export ban is in place to be associated with an even lower relative price for maize. This suggests that an increase in yield have a larger dampening effect on maize prices relative to other crops when a maize export ban is in place.

Export ban and relative volatility in maize price

Focusing on the volatility in prices, we find a similar pattern to that of price levels as reported in table [3.3]. Overall, Prices are much volatile in periods during which an export ban is in place with maize prices exhibiting a higher volatility. This is likely in response to the low harvest that induce higher crop prices. The effect being much larger for maize because of its widely cultivated nature and heavy dependence. However, since we do not distinguish the direction of the price changes, our estimates show an increase in crop yield to be associated with higher price volatility. This is likely as a result of the dampening effect of yield on prices that increases volatility due to significant drop in prices. In this case though, we do not observe a differential effect on volatility of maize prices.

Export bans, maize prices and its volatility

Restricting the sample to only maize crop, table [3.4] and [3.5] repeat the above analyses against which all subsequent findings are compared. We show that our earlier findings on the association between export ban and maize prices both in magnitude and significance remains unchanged.

	(1)	(2)	(3)	(4)	(5)
	Price (kwh/kg)				
Maize ban	0.0963^{***}	0.0962^{***}	0.0984^{***}	0.0989***	0.0983***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ban*Maize	0.229***	0.231***	0.203***	0.264***	0.264***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Yield (Q/Acre)		-0.0312**	-0.0661***	-0.0580***	-0.0580***
		(0.02)	(0.01)	(0.01)	(0.01)
Yield*ban			0.0525***	0.0534***	0.0534^{***}
			(0.01)	(0.01)	(0.01)
maizexyieldxban				-0.109***	-0.109***
·				(0.01)	(0.01)
laffected					0.000293
					(0.00)
Constant	4.948***	4.949***	4.951^{***}	4.949***	4.949^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	114880	114880	114880	114880	114880

Table 3.2: Export Bans and relative Maize prices

Standard errors in parentheses

	(1)	(2)	(3)	(4)	(5)
	sd of lprice	sd of lprice	sd of lprice	sd of lprice	sd of lprice
Maize ban	0.0112^{***}	0.0113^{***}	0.0113***	0.0113***	0.0108***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ban*Maize	0.0233***	0.0219***	0.0208***	0.0189***	0.0188***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Yield (Q/Acre)		0.0298***	0.0285***	0.0282***	0.0282***
		(0.00)	(0.00)	(0.00)	(0.00)
Yield*ban			0.00202^{**}	0.00199^{**}	0.00202^{**}
			(0.00)	(0.00)	(0.00)
maizexyieldxban				$\begin{array}{c} 0.00342 \\ (0.00) \end{array}$	$\begin{array}{c} 0.00358 \\ (0.00) \end{array}$
laffected					0.000286^{***} (0.00)
					()
Constant	0.158^{***}	0.156^{***}	0.157^{***}	0.157^{***}	0.156^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	115499	115499	115499	115499	115499

Table 3.3: Export Bans and relative volatility of Maize prices

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 3.4.	Evport	Bang	and	Maizo	nricos
Table 5.4.	Export	Dans	and	maize	prices

	(1)	(2)	(3)	(4)
	Price (kwh/kg)	Price (kwh/kg)	Price (kwh/kg)	Price (kwh/kg)
Maize ban	0.227^{***}	0.227^{***}	0.240***	0.226^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Yield (Q/Acre)		-0.0175	0.00695	-0.000119
		(0.01)	(0.02)	(0.02)
Yield*ban			-0.0376***	-0.0260**
			(0.01)	(0.01)
laffected				0.00533***
				(0.00)
Constant	3.278^{***}	3.294^{***}	3.469***	3.471^{***}
	(0.02)	(0.03)	(0.03)	(0.03)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	11447	11447	10724	10724

Standard errors in parentheses

	(1)	(2)	(3)	(4)
	sd of lprice	sd of lprice	sd of lprice	sd of lprice
Maize ban	0.0370^{***}	0.0370^{***}	0.0460^{***}	0.0436***
	(0.00)	(0.00)	(0.00)	(0.00)
Yield (Q/Acre)		-0.000494	0.0141^{***}	0.0129^{***}
		(0.00)	(0.00)	(0.00)
Yield*ban			-0.0244^{***}	-0.0224^{***}
			(0.00)	(0.00)
1 00 1				
laffected				0.000918^{***}
				(0.00)
0	0.040***	0.040***	0.00.1***	0.005***
Constant	0.242^{****}	0.243***	0.294	0.295
	(0.00)	(0.00)	(0.00)	(0.00)
	37	37	3.7	37
Time fixed effects	Yes	Yes	Yes	Yes
Observations	11453	11453	10730	10730

Table 3.5: Export Bans and volatility of Maize prices

* p < 0.10, ** p < 0.05, *** p < 0.01

Demand induced vs supply induced export ban

Table [3.6] presents our results once we dis-aggregate the ban into demand induced and supply induced export ban using the full sample. The table estimates a similar version of models [3.4], [3.2] and [3.3] using the full sample. Our findings reveal demand induced export bans to be associated with a higher overall price and an even higher price for maize, maize price increasing almost twice the increase for other crops. On the other hand a supply induced export ban is associated with a relatively lower overall increase in prices albeit a much larger increase for maize prices.

Once we restrict the sample to only the maize crop, our findings are similar as can be seen from table [3.7]. We observe a demand induced export ban to be associated with a larger increase in domestic maize prices, about 30 percent compared to a relatively lower relationship with a supply induced export ban, about 17 percent. However, we now find some how counter intuitive relationship between the yield and prices. An increase in yield seems to be associated with higher prices. For both a demand induced and a supply induced export ban, an increase in yield in the presence of either of the bans is associated with lower relative maize prices.

Instrumental variable results

In this section we present the results from instrumenting the ban with rainfall and global maize prices. Table [3.8] shows the result from considering ban on aggregate using only rainfall in the first specification and in the second specification using both rainfall and global maize prices. Both the first stage and second stage outputs are reported. The results reveal a negative but

	(1)	(2)	(3)	(4)
	Price (kwh/kg)	Price (kwh/kg)	Price (kwh/kg)	Price (kwh/kg)
demand	0.162^{***}	0.162^{***}	0.158^{***}	0.158^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
maizexdemand	0.273***	0.277^{***}	0.269***	0.540***
	(0.01)	(0.01)	(0.01)	(0.05)
supply	0.0304***	0.0304***	0.0385***	0.0300***
	(0.01)	(0.01)	(0.01)	(0.01)
maizexsupply	0.215***	0.216***	0.189***	0.294***
•	(0.01)	(0.01)	(0.01)	(0.02)
Yield (Q/Acre)		-0.0323**	-0.0692***	-0.0555***
		(0.02)	(0.01)	(0.01)
Yield*demand			0.0245^{***}	0.0260***
			(0.01)	(0.01)
Yield*supply			0.0557***	0.0570***
			(0.01)	(0.01)
Yield*demand*Maize				-0.378***
				(0.06)
Yield*supply*Maize				-0.184***
				(0.02)
laffected				0.000866***
				(0.00)
Constant	5.025***	5.026^{***}	5.020***	5.023***
	(0.01)	(0.01)	(0.01)	(0.01)
moi*	Yes	Yes	Yes	Yes
annee*	Yes	Yes	Yes	Yes
N	114880	114880	114880	114880
r2_o	0.0904	0.135	0.161	0.140

Table 3.6: Export Bans by nature and relative Maize prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Price (kwh/kg)	Price (kwh/kg)	Price (kwh/kg)	Price (kwh/kg)	lprice_sd	lprice_sd	lprice_sd	lprice_sd
demand	0.296***	0.296***	0.416***	0.405^{***}	0.377***	0.377***	0.411***	0.379^{***}
	(0.01)	(0.01)	(0.04)	(0.04)	(0.00)	(0.00)	(0.01)	(0.01)
supply	0.163***	0.163^{***}	0.194^{***}	0.169***	0.381***	0.381^{***}	0.450^{***}	0.376***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Yield (Q/Acre)		-0.0176	0.0672^{***}	0.0646^{***}		-0.00186	0.187^{***}	0.179^{***}
(, , , ,		(0.01)	(0.02)	(0.02)		(0.00)	(0.03)	(0.03)
							, ,	. ,
Yield*demand			-0.164***	-0.149***			-0.0453***	-0.00144
			(0.05)	(0.05)			(0.01)	(0.02)
Yield*supply			-0.131***	-0.128***			-0.295***	-0.284***
			(0.02)	(0.01)			(0.03)	(0.03)
laffected				0.00638^{***}				0.0184^{***}
				(0.00)				(0.00)
								. ,
Constant	3.334***	3.350***	3.364^{***}	3.392***	2.502^{***}	2.504^{***}	2.535^{***}	2.617^{***}
	(0.02)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
moi*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
annee*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11447	11447	11447	11447	11453	11453	11453	11453
r2_0	0.682	0.682	0.685	0.687	0.568	0.568	0.576	0.591

Table 3.7: Export Bans by nature and relative Maize prices

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

statistically insignificant effect of the ban on maize prices once we use only rainfall to instrument the ban. If we also account for the fact that the ban may also be induced by external factors and add global maize prices as an instrument for the ban, we instead find a positive and significant effect of the ban on maize prices. On the contrary, we find strong evidence that the ban reduces the volatility of maize prices as can be seen from table [3.10].

In Table [3.11], I report the first and second stage results from distinguishing the ban into demand and supply induced and use rainfall and global prices as instruments. We find that the ban is able to lower prices given a supply induced ban. However, for a demand induced ban, the export ban is unable to lower prices and hence maize prices remain high despite the ban. We attribute this somehow unexpected results to the difficulty in effectively implementing the ban, its porous borders and the unscrupulous activities of traders who hoard the goods when international prices are sufficiently high in anticipation of a lifting of the ban, makes the ban ineffective.

	(1)	(2)	(3)	(4)	(5)	(6)
	Maize ban	Price (kwh/kg)	Maize ban	Yield*ban	Maize ban	Price (kwh/kg)
Yield (Q/Acre)	-0.371^{***}	-0.0946***	-0.00396	0.554^{***}	-0.367***	-0.0530
	(0.05)	(0.04)	(0.00)	(0.06)	(0.05)	(0.03)
Yield*ban	0.663***	0.146^{***}			0.655***	0.0716^{*}
	(0.05)	(0.04)			(0.05)	(0.04)
laffected	0.0115***	0.00760***	0.0112***	-0.000733***	0.0116***	0.00636***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LRain	-0.0569***		-0.0715***	-0.0249***	-0.0551***	
	(0.00)		(0.00)	(0.00)	(0.00)	
Maize ban		-0.0198				0.0897^{*}
		(0.05)				(0.05)
Lglobal			0.00187***	0.00228***	0.000373**	
0			(0.00)	(0.00)	(0.00)	
moi*	Yes	Yes	Yes	Yes	Yes	Yes
Ν	9555	9555	9555	9555	9555	9555
r2	0.316	0.205	0.0920	0.223	0.316	0.235

Table 3.8: Instrumental variable estimation for maize prices

	()	(-)	(-)	()	()	(-)
	(1)	(2)	(3)	(4)	(5)	(6)
	(1st stage)	(2nd stage)	(1st stage)	(2nd stage)	(1st stage)	(1 stage)
	Maize ban	$Price \; (kwh/kg)$	Maize ban	$Price \; (kwh/kg)$	Maize ban	Yield*ban
Yield (Q/Acre)	-0.371^{***}	-0.0946***	-0.367^{***}	-0.0530	-0.00396	0.554^{***}
	(0.05)	(0.04)	(0.05)	(0.03)	(0.00)	(0.06)
Yield*ban	0.663***	0.146^{***}	0.655***	0.0716^{*}		
	(0.05)	(0.04)	(0.05)	(0.04)		
laffected	0.0115***	0.00760***	0.0116***	0.00636***	0.0112***	-0.000733**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LRain	-0.0569***		-0.0551***		-0.0715***	-0.0249***
	(0.00)		(0.00)		(0.00)	(0.00)
Maize ban		-0.0198		0.0897^{*}		
		(0.05)		(0.05)		
Lglobal			0.000373^{**}		0.00187^{***}	0.00228***
0			(0.00)		(0.00)	(0.00)
moi*	Yes	Yes	Yes	Yes	Yes	Yes
Ν	9555	9555	9555	9555	9555	9555
r2	0.316	0.205	0.316	0.235	0.0920	0.223
F	170237.4	134.7	60320444.1	141.4	2.39817e + 09	432.2

Table 3.9: Instrumental variable estimation for maize prices

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 3.10:	Instrumental	variable	estimation	for	maize	price	volatility
10010 0.10.	111001 annonioan	variabio	countation	TOT	manzo	PIICO	1010011109

	(1)	(2)	(3)	(4)
	Maize ban	lprice_sd	Maize ban	lprice_sd
Yield (Q/Acre)	-0.371***	-0.184***	-0.367***	-0.147***
	(0.05)	(0.04)	(0.05)	(0.04)
Yield*ban	0.663***	0.345***	0.655***	0.278***
	(0.05)	(0.05)	(0.05)	(0.06)
laffected	0.0115***	0.0276***	0.0116***	0.0264***
	(0.00)	(0.00)	(0.00)	(0.00)
LRain	-0.0569***		-0.0551***	
	(0.00)		(0.00)	
Maize ban		-0.341***		-0.244***
		(0.06)		(0.07)
Lglobal			0.000373**	
0			(0.00)	
moi*	Yes	Yes	Yes	Yes
Ν	9555	9555	9555	9555
r2	0.316	0.0212	0.316	0.0820

Standard errors in parentheses

	(1)	(2)	(3)	(4)	(5)	(6)
	supply	demand	Price (kwh/kg)	supply	demand	Price (kwh/kg)
Yield (Q/Acre)	-0.00320	-0.000584	-0.0157	-0.304***	-0.0913***	-0.0152
	(0.00)	(0.00)	(0.02)	(0.05)	(0.01)	(0.02)
laffected	0.00991^{***}	0.000992^{***}	0.0113^{***}	0.00978^{***}	0.000912^{***}	0.00983^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IDain	0.0401***	0.09/1***		0.05/1***	0 0009***	
LITAIII	-0.0491	-0.0241		-0.0541	-0.0202	
	(0.00)	(0.00)		(0.00)	(0.00)	
Lglobal	-0.000343***	0.00201***		-0.00165***	0.00155^{***}	
0	(0.00)	(0.00)		(0.00)	(0.00)	
		· · · ·				
supply			-0.432^{***}			-0.285^{***}
			(0.06)			(0.05)
J J			0 500***			0 00 1***
demand			(0.05)			(0.084)
			(0.05)			(0.05)
LRainxvield				0.0105***	-0.00678***	
				(0.00)	(0.00)	
				()		
Lglobalxyield				0.00174^{***}	0.000580^{***}	
				(0.00)	(0.00)	
•*	37	37	37	37	37	37
mol [*]	Yes	Yes	Yes	Yes	Yes	Yes
N	9844	9844	9844	9844	9844	9844
r2	0.113	0.109	0.0895	0.138	0.112	0.116

Table 3.11: Instrumental variable estimation for maize prices

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

Export ban and relative acreage shares

Estimating model [3.5] with OLS and fixed effect gives us the lower and upper bound for our lagged coefficient estimate using System-GMM, these are reported in column [1] and [2] of table [3.12] and includes standard determinants of acreage allocation as have been considered in the literature. This initial estimates shows that acreage share are highly persistent overtime as evidenced by the positive and statistically significant coefficient of our lagged estimates which ranges from about 30 percent with the fixed effect estimator to about 80 percent with the OLS estimator. Turning to our System-GMM estimates in column [3], we estimate this persistence in lagged acreage share to be about 40 percent. Our findings indicate that the imposition of an export ban is associated with an increase share of acreage dedicated to the cultivation of other crops and a decrease in the share of acreage dedicated to maize cultivation. We do find also an increase in the price of other crops in the preceding period decrease the share of acreage allocated to maize production while a higher maize price in the previous period is associated with an increase in maize acreage share in the next period. Similarly, an increase in the yield for other crops is associated with a lower acreage share for maize. These findings are consistent with earlier findings in the literature on acreage allocation decisions under uncertainty, see Chavas and Holt (1990b) on the case of corn and soybeans in the US, Haile et al. (2014) and Haile et al. (2016) on global crop acreage response to crop prices and price risk. Interestingly, we find an increase in maize yield in the previous period to have a negative impact on future acreage share dedicated to maize cultivation. The reason for this is not very clear. However, one may expect that the cultivation of higher yielding maize varieties may indeed reduce the need to allocate more acreage to maize cultivation.

The fact that we use a two-step System GMM estimator and treat past acreage shares, and past yields as endogenous and include annual rainfall and mean annual temperatures as exogenous instruments mitigate endogenity concerns for the effect of a risk generated by an export ban on crop acreage shares. However, we acknowledge that our findings do not shed much light on the channel of transmission of the export bans on farmers acreage response. In particular, we acknowledge the following concerns, unlike in many of the previous studies in this literature which considers countries in which there are only a handful of farmers or for whom production is mainly aimed for either domestic or international markets, maize production in Malawi like many countries in the sub-region is mainly done at a small scale and mostly aimed for domestic consumption¹⁸. Therefore, though we find similar results, the mechanism behind this results might be quite different. For instance tough our finding suggests that farmers respond to the market uncertainty risk by shifting acreage away from maize to other crops, this however may not be the case. It could simply just be that farmers respond to the uncertainties by cultivating more drought resistant, early maturing and higher yielding maize varieties that

 $^{^{18}}$ According to the IHPS 2016 only about 11 percent of Malawian households were selling Maize down from about 13 percent in 2011.

we do not see once we use the aggregate data. Therefore, to investigate this mechanism further, it is imperative to use more micro data that could reveal all these details which would help to better understand household farming decisions.

	(1)	(2)	(3)	(4)
	share	share	share	share
L.share	0.840^{***}	0.313**	0.412^{**}	0.412^{**}
	(0.0142)	(0.157)	(0.165)	(0.165)
ban	0.00703	0.0160*	0.116**	0.116**
	(0.00810)	(0.00924)	(0.0500)	(0.0504)
maizexban	-0.0400***	-0.0455***	-0.0664**	-0.0663**
	(0.00653)	(0.0165)	(0.0314)	(0.0310)
	()	()	()	()
Lprice	-0.00301	-0.000715	-0.106***	-0.108**
	(0.00243)	(0.00294)	(0.0398)	(0.0455)
maizexLprice	0.0184^{***}	-0.0508**	0.0812^{***}	0.0826^{***}
	(0.00329)	(0.0235)	(0.0107)	(0.0135)
Lvield	0.000195	0.0000610	-0.00641*	-0.00623**
v	(0.000242)	(0.000841)	(0.00340)	(0.00304)
	× ,	· · · ·		· · · ·
Lyieldxmaize	0.000726	-0.0273	-0.103***	-0.105^{***}
	(0.00543)	(0.0191)	(0.0293)	(0.0319)
Constant	0.0203*	0.0699***	0.452^{*}	0.454**
	(0.0119)	(0.0232)	(0.236)	(0.219)
	()	()	()	()
$annee^*$	Yes	Yes	Yes	Yes
Observations	1455	1455	1455	1361
No. of groups		95	95	95
AR1 (p-value)			0.0258	0.0180
AR2 (p-value)			0.888	0.972
Hansen-J (p-value)			0.261	0.212

Table 3.12: Export Bans and relative Acreage shares

Standard errors in parentheses

* pj0.10, ** pj0.05, *** pj0.010

3.7 Conclusion

Increasing concerns about food security have led many governments of major exporting and non-major exporting countries to adopt a series of trade restrictions aimed at ensuring food security (Sharma (2011)). In Malawi like in many other east and southern African countries, maize is a major staple commodity that is widely cultivated and consumed in the region. Data from EM-DAT shows that the region is quite susceptible to weather shocks which makes crop production quite volatile. In response to this, the government of Malawi sometimes intervene in the market to restrict the export of maize abroad in periods when output are projected to be low or are actually low and or when their is rising global demand. This is aimed at ensuring food security and shielding its populace from rising global prices. In this chapter, we have attempted to evaluate the effectiveness of these series of trade restrictions in the form of maize export bans on domestic maize prices and its volatility as well as on food security proxied here by the share of acreage allocated to maize cultivation. Furthermore, we extend this literature by categorising bans into demand induced vs supply induced export bans. We use monthly price crop data on various markets and annual production data from the Malawian Ministry of Agriculture and water development for the period 1998 to 2019 to estimate the effect of these policies. To address concerns about the endogeneity of export bans we use two exogenous variables to instrument the ban. We use monthly rainfall and its interaction with yield per acre to instrument a supply induced export ban. While for a demand induced export ban, we use monthly global corn prices and its interaction with yield per acre. Both instruments are plausibly exogenous. We rely on a series of test to confirm this.

Our findings indicate that export bans are ineffective in preventing a rise in domestic prices once we group all bans together in line with some findings such as Garcia-Lembergman et al. (2017). Instead, we find robust evidence that the ban reduces the volatility of maize prices. Once we dis-aggregate the ban into demand induced and supply induced, we observe a differential effect of the ban on maize prices. This highlights that our previous findings were masked by this differential effects. We find robust evidence that export bans are effective in lowering domestic maize prices if the ban is induced by a supply shock. On the contrary, export bans are ineffective in shielding domestic prices from external demand shocks. Despite the ban, domestic maize prices are considerably higher. This raise concerns about the effective implementation of the policy considering the porous nature of its borders, the difficulty in controlling a large number of small growers and traders and potential actions of traders in response to the ban.

Treating the unpredictability of the export bans as a source of market risk, we investigate the effect of this uncertainty on maize production by specifically studying the acreage share allocated to maize cultivation. Earlier findings by Aragie et al. (2018) and Garcia-Lembergman et al. (2017) also highlighted a potential supply shift in response to such restrictions. Our findings reveal that average share allocated to maize cultivation reduces in response to an export ban. However, we acknowledge that due to the aggregate nature of our data we are unable to shed light about any potential dynamics that may be taking place such as a shift from cultivating low yielding local varieties to higher yielding improved varieties. We therefore suggest that further research into this area should use micro level data to better shed light on farmers response to such market uncertainty.

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