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Climate Shocks, Migration, and Labor Markets: A Gender Analysis from West Africa*

Nelly Elmallakh [†] and Quentin Wodon [‡]

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Abstract

This paper investigates the effects of shocks, predominantly climate shocks, on labor market outcomes in the West African Economic and Monetary Union (WAEMU). We focus on migration flows within the WAEMU countries to disentangle the differential effects of shocks on migrants and non-migrants. Our analysis combines survey data from Ivory Coast—as the main migrant receiving country—and from all the other 7 migrant sending countries of the WAEMU. Using an OLS fixed effects model, our results show that migration in the WAEMU is associated with a decline in female labor participation, as it is primarily motivated by marriage. However, we find an increase in female labor force participation and a narrowing of the gender gap in migrant households that are negatively affected by shocks. Our findings relate to the literature on the impact of shocks on the labor division between women and men and show that shocks may disrupt long-standing gender roles. The results are robust to accounting for the double selection into shocks and migration using a Propensity Score Matching technique that allows for a within comparison between treated and untreated units.

Keywords: shocks, migration, climate, employment, labor market, women, West Africa.

JEL codes: F22, J21, J43, J61, Q54.

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1 Introduction

Political, environmental, and climate shocks can undermine welfare and livelihoods. Weather and climate shocks can be particularly detrimental to agricultural and resource-dependent households and their effects might be magnified by exposure to additional political shocks. West Africa is a case in point. On one hand, the semi-arid countries of West Africa face a multitude of climate shocks and, most importantly, are drought-prone. According to the *Enquête Harmonisée sur les Conditions de Vie des Ménages* (EHCVM) conducted across all countries of the West African Economic and Monetary Union (WAEMU), drought is one of the most frequent climate-related disasters occurring across large portions of West Africa. Burkina Faso and neighboring Sahel countries, such as Mali and Niger, are the most affected, with as high as 36% of households being negatively affected by these devastating shocks. On the other hand, several countries in West Africa are also prone to political violence and armed conflict. A recent OECD report highlights that almost three-quarters of the West African countries have been involved in an armed struggle since 1960 and that while in recent decades the region witnessed a decline in inter-state violence, intra-state conflicts have engulfed several countries (OECD, 2020).

In this paper, we investigate the effect of shocks on labor market outcomes in the WAEMU from a gender perspective. The shocks we take into consideration are by and large climate related (droughts, floods, fires, and landslides), though a small proportion of our sample experienced political shocks, such as armed conflict and violence. We ask whether shocks can have differential effects among migrant and non-migrant households in West Africa. We focus on Ivory Coast as the main migrant receiving country in the WAEMU, as immigrants from the WAEMU constitute 17% of the population in Ivory Coast. One of the main novelties of this paper is that it combines data on WAEMU immigrants in Ivory Coast (immigrants from Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo), as well as data on non-migrants in each of the WAEMU countries. This allows us to compare international migrants and non-migrants from the same origin countries. In what follows, we will refer to international migration simply as migration since we focus solely on international migrants, from WAEMU countries to Ivory Coast, and not on internal migrants.

A significant proportion of female migration in Ivory Coast from the other WAEMU countries is composed of moves by women for the purpose of marriage, while male migration is primarily economic in motivation. Our analysis of the EHCVM surveys indicates that 67% of women migrated to Ivory Coast due to marriage, while 56% of men reported better opportunities in Ivory Coast as their primary migration motive. These differences have important implications when it comes to migrant women's participation in the labor market. While the labor force participation of women is always lower than that of men, migrant women in West Africa are found to have a lower labor

force participation rate compared to the average non-migrant woman. These differences may reflect vastly different economic opportunities for women, carry implications on the role of women in society, and can have implications on children’s education and future outcomes through inter-generational transmission of human capital.

The importance of female marital migration is not confined to West Africa. For instance, [Rosenzweig and Stark \(1989\)](#), who analyzed the 1981 Population Census in India, have shown that 80 percent of migrants (individuals who resided in a place other than their place of birth) were women who reported that marriage was the principal reason for their move. Likewise, [J. P. Smith and Thomas \(1998\)](#), in their analysis of the 1988/1989 Malaysia Family Life Survey, found that three-quarters of women migrated for the first time across district boundaries after they married.

Climate shocks, on the other hand, have been shown to affect productivity, employment, and labor markets. For instance, [Jessee, Manning, and Taylor \(2018\)](#) evaluate the effects of annual fluctuations in weather in rural Mexico and find that years with a high occurrence of heat are associated with a decline in local employment. Likewise, [Minale \(2018\)](#) estimates a 4.5% decline in farming in response to a one standard deviation negative rainfall shock in rural India, while [Aragón, Oteiza, and Rud \(2021\)](#) and [Letta, Montalbano, and Tol \(2018\)](#) find that extreme heat and temperature shocks are associated with a reduction in agricultural productivity in Peru and rural Tanzania, respectively.

Given the importance of both female migration and shocks, and the implications they might have on women’s empowerment and their role in society, we examine the differential effects of shocks on migrant and non-migrant women and men, focusing on labor market outcomes such as labor force participation, employment, and unemployment. We also explore intra-household differences in labor market outcomes in order to assess the size of the gender gap between a woman and her partner. Accounting for country-level time invariant heterogeneity and controlling for a wide range of individual covariates using an OLS fixed effects model, our results show an increase in female labor force participation and employment in migrant households that are negatively affected by shocks. While migration is associated with a widening of the gender gap in labor force participation and employment, we find that shocks are associated with a narrowing of the gender gap in migrant households. Examining the effects by economic activity, we find an increase in female employment in personal services in migrant households that are negatively affected by shocks.

We also provide convincing evidence that neither selection into shocks nor selection into migration is driving our results. Following [Abadie and Imbens \(2006\)](#) and [Caliendo and Kopeinig \(2008\)](#), we use a Propensity Score Matching (PSM) technique that allows us to pair treated individuals (those who witnessed shocks) with untreated individuals (those who did not witness shocks) who have similar values of the propensity score. Based on the matched sample of treated and untreated observations, we estimate our

OLS fixed effects model by including a set of fixed effects for each pair of matched observations to allow for a within comparison between treated and untreated units with similar propensity score values. We also deal with the additional selection into migration, by performing a “double Propensity Score Matching technique” to match migrants and non-migrants with similar values of the propensity score. Likewise, this technique allows for a within comparison between each pair of matched migrant and non-migrant. Our estimates are therefore purged out of any additional unobservable heterogeneity for a pair of matched individuals/households along these two selection dimensions and are robust to accounting for the double selection into shocks and migration.

Our paper is related to several strands of the literature. First, the paper fits within the broad body of research on shocks and female labor force participation. It is well-established in the literature that women’s labor supply responds to various political, technological, economic, and demographic shocks. For instance, [Goldin \(1991\)](#), [Acemoglu, Autor, and Lyle \(2004\)](#), and [Goldin and Olivetti \(2013\)](#) show a persistent increase in women’s labor supply following World War II. Likewise, medical and technological progresses have been associated with increases in female labor force participation ([Albanesi & Olivetti, 2016](#); [Greenwood, Seshadri, & Yorukoglu, 2005](#)). Moreover, other studies show long-term changes in women’s labor supply as a consequence of economic and demographic shocks ([Fogli & Veldkamp, 2011](#); [Grosjean & Khattar, 2019](#); [Teso, 2019](#)). Likewise, [El-Mallakh, Maurel, and Speciale \(2018\)](#) document an increase in women’s labor force participation and a reduction in the gender gap following the Arab Spring uprisings.

Second, our paper also relates to the literature on how poor households cope with shocks. While rural households often rely on informal insurance arrangements to smooth their consumption in the face of short-term idiosyncratic income shocks ([Ravallion & Chaudhuri, 1997](#); [Townsend, 1994](#)), they rely on different coping strategies in order to face aggregate shocks. For instance, the liquidation of buffer stocks has been hypothesized as one of the coping strategies on which rural households rely to insulate their consumption from fluctuations in income ([Acosta, Nicolli, & Karfakis, 2021](#); [Binswanger, McIntire, & Udry, 1991](#); [Bromley & Chavas, 1989](#); [Do, Nguyen, & Grote, 2019](#); [Fafchamps, Udry, & Czukas, 1998](#); [Hänke & Barkmann, 2017](#); [Lange & Reimers, 2021](#)). Moreover, it has been well-documented in the literature that households rely on seasonal migration when hit by negative shocks. Several studies document the use of internal or transnational migration as a risk management strategy to insure against agricultural risk due to climate and weather-related shocks (see for instance, [Morten \(2019\)](#) on India; [Gray and Mueller \(2012\)](#) on Ethiopia; [Dillon, Mueller, and Salau \(2011\)](#) on Nigeria; [Koubi, Spilker, Schaffer, and Bernauer \(2016\)](#) on Vietnam; [Halliday \(2006\)](#) on El Salvador; [Giles \(2006\)](#) on China). Relatedly, [Yang and Choi \(2007\)](#) and [Calero, Bedi, and Sparrow \(2009\)](#) show that remittances sent by overseas migrants

serve as an insurance for recipient households facing income shortfalls. Crop diversification, labor diversification, and off-farm employment are other well-documented strategies on which households rely in response to unfavorable agricultural production environments (Asfaw, Pallante, & Palma, 2018; Bozzola & Smale, 2020; Chuang, 2019; Demeke & Zeller, 2012; Gao & Mills, 2018; Ito & Kurosaki, 2009; Mathenge & Tschirley, 2015; Mulwa & Visser, 2020). Finally, other studies have shown that households facing economic strain due to adverse shocks may consider marrying off their daughters as a coping strategy. This practice has been shown to be particularly prevalent in societies that engage in bride price payments (Corno, Hildebrandt, & Voena, 2020; Corno & Voena, 2016; Rosenzweig & Stark, 1989; Trinh & Zhang, 2020). In this paper, we show that migrant households rely on female labor as a strategy to cope with negative shocks, whether in the form of political or climate shocks. In their comprehensive conceptual framework on household resilience capacities, L. C. Smith and Frankenberger (2018) have advanced women’s empowerment as one of the factors reducing the negative impact of shocks, highlighting that women’s empowerment is expected to increase households’ overall capacities to respond to shocks and stressors. While this channel was only hypothesized conceptually in the existing literature, this paper provides the first empirical evidence supporting women’s empowerment as a household resilience strategy in the face of climate shocks. Indeed, we show that while migrant women primarily move for the purpose of marriage, exposure to shocks seems to lead to greater female engagement in the labor market, contesting traditional views about the role of women in society.

The rest of this paper is organized as follows: section 2 describes the data and presents some stylized facts. Section 3 presents the conceptual framework and the empirical model. Section 4 discusses the empirical results, while section 5 presents robustness checks. Finally, section 6 concludes.

2 Data and Stylized Facts

2.1 The EHCVM Surveys

We rely on data from the *Enquête Harmonisée sur les Conditions de Vie des Ménages* (EHCVM). The EHCVM surveys are nationally representative surveys administered across all WAEMU countries. The surveys were conducted in two waves in 2018 and 2019 with the financial support of the World Bank and in cooperation with the WAEMU Commission. The EHCVM surveys provide information on individual socio-demographic characteristics, education, and labor market outcomes. And importantly, the EHCVM surveys provide information on individuals’ nationality which allows us to identify international migrants, as well as their origin countries. More generally, the surveys provide information on savings, consumption, food security, agricultural

output, non-agricultural enterprises, housing characteristics, and household assets.

In our analysis, we focus on Ivory Coast as the main migrant receiving country in the WAEMU. Indeed, as we show in Figure 1 in Panel A, the national population in Ivory Coast stands at 82% according to the EHCVM survey in Ivory Coast, while almost 17% of the population are migrants from the WAEMU.¹ We further present in Figure 1 in Panel B the nationality breakdown for all WAEMU migrants in Ivory Coast. We find that all countries in the WAEMU are represented in the migrant population in Ivory Coast. Migrants come predominantly from Burkina Faso and Mali. Figure 2 features a map of West Africa in which Ivory Coast, the main migrant receiving country, is presented in green, while all the other WAEMU migrant sending countries are presented in orange. Indeed, according to the EHCVM surveys, the share of migrant population in each of the other WAEMU countries stands at 2% or less.²

Since our objective is to examine the effect of shocks on migrants and non-migrants, our sample includes WAEMU migrants in Ivory Coast, as well as nationals (non-migrants) in each of the remaining 7 countries of the WAEMU. Restricting our analysis to nationals of these 7 WAEMU countries—residing in either Ivory Coast or in their origin countries—allows us to compare migrants and non-migrants of the same nationalities. We therefore rely on the EHCVM surveys conducted across all 8 WAEMU countries: Benin, Burkina Faso, Guinea-Bissau, Ivory Coast, Mali, Niger, Senegal, and Togo. Our sample consists of pooled cross-sectional data utilizing all the surveys administered in the 8 WAEMU countries. We rely on the EHCVM survey in Ivory Coast to collect information on WAEMU migrants, while we rely on the EHCVM surveys in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo to collect data on nationals (non-migrants).

2.2 Shocks in the WAEMU

The EHCVM surveys have a specific module on shocks witnessed by households. Individuals were asked if they were negatively affected by certain shocks in the three years preceding the survey. In our analysis, we focus on exogenous shocks such as those related to climate and armed conflict. Climate shocks include: droughts/irregular rain, floods, fires, and landslides, while shocks related to conflict include armed conflict, violence, and insecurity which are grouped in one category in the survey.

In the Online Appendix Table A.1, we present the incidence of conflict and climate shocks in each of the WAEMU countries. Ivory Coast refers to the sample of migrants,

¹ Other migrant nationalities in Ivory Coast include Nigeria, other countries in the Economic Community of West African States (ECOWAS), other countries in Africa, and other countries outside Africa.

² Following Ivory Coast, the WAEMU country with the highest share of migrant population is Togo. According to the EHCVM data, the share of migrant population in Togo is 2.07%, followed by Benin (1.61%), Guinea-Bissau (1.38%), Senegal (0.99%), Niger (0.91%), Mali (0.38%), and Burkina Faso (0.34%).

while each of the other countries refers to the national population in the corresponding country. Focusing on working age individuals in Table A.1 as in our estimations, we derive several important findings. First, we find that droughts/irregular rain is by far the most prevalent shock that negatively affects individuals. This is consistently the case across all WAEMU countries. Second, we find that the prevalence of armed conflict/violence/insecurity is rather low. Indeed, we find that less than 1% of individuals in each country were negatively affected by conflict (the surveys were implemented before the recent rise in attacks by extremist groups in some of the countries, especially in the Sahel). Finally, we find that the countries with the highest share of individuals affected by any shock are those countries with the highest shares of migrant population in Ivory Coast. Mali, Burkina Faso, and Niger are the countries with the highest shares of individuals negatively affected by conflict and climate shocks—and they are also the top three countries sending migrants to Ivory Coast. Overall, the distribution of shocks in Table A.1 closely mimics the distribution of countries in Figure 1 in Panel B, with a highest share of emigration in countries witnessing a greater incidence of shocks.

Although we do not have information on the year of migration to identify whether individuals migrated before or after being negatively affected by shocks, migrants in Ivory Coast were asked about the reasons of migration, which include natural disasters, armed conflict, and political/economic instability. According to the EHCVM data in Ivory Coast, less than 1% of individuals migrated due to one of these factors. Based on this piece information, we can infer that migrants in Ivory Coast who were negatively affected by shocks witnessed these shocks in the destination rather than responded to shocks in their origin countries by migrating.

In Table 1 and Table 2, we report descriptive statistics by exposure to shocks on women and men, respectively. The analysis is restricted to the working age population. We examine differences between individuals who witness shocks and those who do not witness any, in terms of individual characteristics, education, religion, as well as countries of origin. Throughout our analysis, we consider that individuals/households are exposed to shocks if they reported being negatively affected by a given shock in the three years preceding the survey.

The variables reported in Table 1 and Table 2 correspond to the vector of controls included in our benchmark regression model. We find important differences between individuals that reported being negatively affected by shocks and those who did not. Indeed, we find that both women and men that reported being negatively affected by shocks in the three years preceding the survey are significantly more likely to be married and to reside in rural areas, compared to individuals who did not witness any shocks. Moreover, we find that individuals who were negatively affected by shocks have a lower educational profile relative to those who were not affected by shocks. Indeed, the incidence of having no educational degree is 15 percentage points and 18

percentage points higher among individuals who witnessed shocks versus those who did not, for women and men, respectively. This is likely related to the fact that shocks, such as droughts or irregular rain, tend to affect subsistence farmers the most, and those tend to be poorer and less well educated. Moreover, we find that individuals who witnessed shocks are more likely to be Muslim relative to those who did not witness shocks. As for countries of origin, we find that individuals who reported being negatively affected by shocks are more likely to be nationals of Burkina Faso, Mali, and Niger. This is consistent with the descriptive statistics reported in Table A.1 in the Online Appendix.

2.3 Stylized Facts

Relying on data from the EHCVM surveys, we compute male and female employment rates, by migration status. Focusing on working age individuals, we compare the employment rates of migrants relative to non-migrants. In Figure 3, we plot male employment rates in Panel A, while we plot female employment rates in Panel B. We consistently find higher employment rates among migrant men relative to non-migrants. Indeed, nationals of all WAEMU countries in Ivory Coast have higher employment rates compared to their peers who remained in their origin countries. As for women, we generally find the opposite pattern. On average, migrant women seem to have lower employment rates relative to non-migrant women. Although migrant women’s employment rates are higher among nationals of Benin, Guinea-Bissau, and Mali, the difference between migrant and non-migrant employment rates in this set of countries is rather small relative to the large negative gap between migrant and non-migrant women in the other countries.

These differences between male and female employment rates among migrants and non-migrants seem to be driven by the reasons of migration, which are substantially different by gender. The EHCVM surveys provide information on the reasons of migration which include: being sent by family for work, migrating with parents, following or joining family, lack of employment, better opportunities in destination, marriage, as well as other reasons.³ As shown in Figure 4, while men predominantly migrated seeking better opportunities (55.9%), we find that the majority of women migrated due to marriage (67%). The second most common reason for which women migrated is to follow or join family (18%). A similar share of men migrated for the same reason. Moreover, we find that only 4.9% of women migrated for better work opportunities. These gendered migration patterns might explain the differential employment rates that we observe when comparing employment rates by gender and migration status.

We further explore in Figure 5 employment and unemployment rates among mi-

³ Other reasons include assignment, lack of land, school, divorce, loss of spouse, illness of a household member, other family problems, armed conflicts, political or economic instability, and natural disasters.

grants and non-migrants, by exposure to shocks. Although, Figure 3 shows that male employment rates are higher among migrants relative to non-migrants, we find in Figure 5 little variation in male employment rates by exposure to shocks (Panel A). Indeed, both migrant and non-migrant men who were exposed to shocks have comparable employment rates relative to those who were not negatively affected by shocks. Similarly, we find substantially lower unemployment rates among migrant men relative to non-migrants, also with little variability by exposure to shocks (Panel B). However, we find that the unemployment rates among non-migrant men are slightly higher when being negatively affected by shocks, while the opposite is true among migrants.

Different patterns arise when examining women’s employment and unemployment rates by exposure to shocks. Our previous analysis led us to establish the fact that women’s employment rates are lower among migrant relative to non-migrant women. On the other hand, the descriptive analysis provided in Figure 5 in Panel A shows that the employment rate among migrant women increases in the presence of shocks, while women’s employment rate drops among non-migrant women when exposed to shocks. While negative shocks seem to adversely affect non-migrant women, shocks seem to be associated with an increase in employment among migrant women. As we show in Panel B, the increase in migrant women’s employment in the presence of shocks seems to also coincide with a large decline in migrant women’s unemployment rates.

3 Conceptual and Empirical Models

3.1 Conceptual Framework

We rely on a simple conceptual framework for the empirical analysis to follow. Nationals of the WAEMU face a decision to either stay in their home country or to migrate. Ivory Coast is the country with the highest share of migrant population. As presented in section 2.1, 17% of the population in Ivory Coast consists of immigrants. On the other hand, all the remaining countries in the WAEMU have very small immigration rates. Following Ivory Coast, the country with the highest share of migrant population is Togo. According to the EHCVM data, the share of migrant population in Togo is 2.07%, followed by Benin (1.61%), Guinea-Bissau (1.38%), Senegal (0.99%), Niger (0.91%), Mali (0.38%), and Burkina Faso (0.34%).

For simplicity, we therefore consider a dichotomous choice between staying in the home country or migrating to Ivory Coast. These locational choices are denoted by $l_i \in \{\text{WAEMU}, \text{CIV}\}$, while the migration decision is denoted by M_i . In our model, the WAEMU corresponds to all WAEMU countries except Ivory Coast. Within this static model, individuals can be subject to negative shocks, which we denote by S_i , in each of these locations (WAEMU versus CIV). As we discussed in section 2.2, the EHCVM survey provides evidence that migrants in Ivory Coast did not migrate due to

shocks, as less than 1% of migrants reported migrating due to natural disasters, armed conflict, or political/economic instability. This suggests that both migrants and non-migrants witness these shocks in their destination and origin countries, respectively. According to this simple conceptual framework, individuals can therefore belong to one of 4 states: (i) $M_i=0$ and $S_i=0$, (ii) $M_i=0$ and $S_i=1$, (iii) $M_i=1$ and $S_i=0$, and (iv) $M_i=1$ and $S_i=1$.

To model these various states, we combine data from both migrant receiving and migrant sending countries in the WAEMU. To estimate the first two states (i) and (ii), we rely on data on national citizens in all WAEMU countries, except Ivory Coast. On the other hand, we model states (iii) and (iv) relying on migrant data from the Ivory Coast survey. We model several labor market outcomes including labor force participation, employment, and unemployment. For a given outcome Y_i , we can therefore estimate the above mentioned 4 states depending on an individual’s migration status and exposure to shocks. In the empirical analysis that follows, we show how we estimate these distinct effects.

3.2 An OLS Fixed Effects Model

Using pooled cross-sectional data collected across all 8 countries of the WAEMU, we ask whether negative shocks have a differential impact on migrants and non-migrants. Combining data on both migrant sending countries (WAEMU) and the migrant receiving country (Ivory Coast), we assess the impact of shocks on labor market outcomes among migrant households in the destination and among non-migrants in the home country. Our empirical model allows us to disentangle a *migration* effect from a *shock* effect, as well as to quantify the differential effect of shocks on migrants. We estimate the following specification using a standard OLS fixed effects model:

$$Y_i = \alpha_1 + \alpha_2 \text{Migrant}_i \times \text{Shock}_i + \alpha_3 \text{Shock}_i + \alpha_4 \text{Migrant}_i + \alpha_5 X_i + \varepsilon_i \quad (1)$$

We estimate the effect of shocks on various outcomes denoted by Y_i . The main independent variables of interest are dummy variable indicators for: (i) labor force participation, (ii) employment, and (iii) unemployment.⁴ We estimate these regressions on women and men, separately. Focusing on working age individuals (15 to 64 years old), we define employed individuals as those who worked at least one hour in the week preceding the survey or had a job but did not work due to being on vacation, leave, sick leave, etc. Employment includes wage work, self-employment, and unpaid family work.

⁴ We also report the results using a probit model in the Online Appendix A.4. The estimates using an OLS fixed effects model in Table 3 are very similar in magnitude to the probit model estimates presented in Table A.4. We rely on the OLS fixed effects model as our benchmark model for computational reasons due to the large number of fixed effects included in the Propensity Score Matching model presented in section 3.4.

We define unemployed individuals as those who engage in subsistence economic activities (without remuneration) but are actively searching for employment or as those who are not engaged in any activity but are actively searching for employment. We also define as unemployed those who are not actively searching for a job but are waiting for a response on a job application and are immediately available to work. An individual participates in the labor market if that individual is either employed or unemployed. We also examine the effect of shocks on other outcomes, conditional on employment, such as sectors of employment, and economic activities.

The variable $Shock_i$ is a dummy variable indicator for past exogenous shocks. It is equal to 1 if the household reported being negatively affected by shocks in the three years preceding the survey. We focus on climate shocks such as droughts/irregular rain, floods, fires, and landslides, as well as shocks related to violence which include armed conflict/violence/political instability. $Migrant_i$ is a dummy variable equal to 1 for migrants in Ivory Coast from all WAEMU countries and equal to zero for national citizens in the remaining WAEMU countries.

Our regressions control for a wide range of individual covariates. The vector X_i includes the following controls: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Since our sample in Ivory Coast is restricted to the migrant population, the $Migrant_i$ dummy is equivalent to including a dummy variable for Ivory Coast.⁵

In addition to looking at the effects of shocks and migration, a key variable is the interaction term between the shock dummy and the migrant dummy. The estimated coefficient α_2 therefore captures the differential effect of shocks among WAEMU migrants in Ivory Coast. Based on equation (1), we can estimate average outcomes based on the four states presented in section 3.1. Relying on equations (2) to (5), we can estimate average outcomes based on an individual's migration status and exposure to shocks.

The average outcome without migration and shocks:

$$E(\bar{Y}|M_i = 0, S_i = 0) = \hat{\alpha}_1 \quad (2)$$

The average outcome without migration and with shocks:

$$E(\bar{Y}|M_i = 0, S_i = 1) = \hat{\alpha}_1 + \hat{\alpha}_3 \quad (3)$$

⁵ In the robustness checks, we additionally include nationals of Ivory Coast in our sample. In these regressions, our country of origin fixed effects additionally include a dummy variable for Ivory Coast. Our results are robust to including Ivory Coast nationals and are reported in Table A.12 and Table A.13 in the Online Appendix.

The average outcome with migration and without shocks:

$$E(\bar{Y}|M_i = 1, S_i = 0) = \hat{\alpha}_1 + \hat{\alpha}_4 \quad (4)$$

The average outcome with migration and shocks:

$$E(\bar{Y}|M_i = 1, S_i = 1) = \hat{\alpha}_1 + \hat{\alpha}_2 + \hat{\alpha}_3 + \hat{\alpha}_4 \quad (5)$$

3.3 Intra-Household Differences in Labor Market Outcomes

Apart from examining the effect of shocks on labor market outcomes for women and men, we also investigate the effect on the gender gap in labor market outcomes. Given the gendered patterns in labor market outcomes presented in section 2.3, we ask whether shocks have a differential effect on the gender gap in migrant and non-migrant households. When modeling the effect on the gender gap, our analysis is therefore restricted to households composed of married couples of working age. We estimate equation (6) relying on an OLS fixed effect model:

$$Y_h = \beta_1 + \beta_2 \text{Migrant}_h \times \text{Shock}_h + \beta_3 \text{Shock}_h + \beta_4 \text{Migrant}_h + \beta_5 X_h + \varepsilon_h \quad (6)$$

$$Y_h = \left\{ \begin{array}{l} -1 \text{ if } Y_w = 0, Y_m = 1 \\ 0 \text{ if } Y_w = 1, Y_m = 1 \mid Y_w = 0, Y_m = 0 \\ 1 \text{ if } Y_w = 1, Y_m = 0 \end{array} \right\} \quad (7)$$

In equation (6), the vector of dependent variables Y_h is defined as intra-household differences in labor market outcomes. For a given outcome, Y_h is equal to the difference between the outcome of the woman (Y_w) and her partner (Y_m). For labor force participation, as presented in equation (7), the dependent variable thus takes the value -1 if the woman is not participating in the labor market and the partner is, 0 if both partners are participating in the labor market or if neither one is, and 1 if the woman is participating in the labor market and the partner is not. The same applies for employment and unemployment. An increase in the value of the dependent variable of interest can be interpreted as a reduction in the gender gap, while a decrease is associated with an increase in the gender gap.

The dummy variables Migrant_h and Shock_h are defined in a similar way as in section 3.2, only that they reflect migration and exposure to shocks at the household level, rather than at the individual level. The vector X_h likewise corresponds to household controls: age of the woman and her spouse, a dummy for rural residence, the educational gap which corresponds to the difference in the highest level of educational attainment between the woman and her spouse (no education, primary or less, secondary, upper secondary, post-secondary and above), and dummies for the religion of the household head (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects for the household head.

A key coefficient of interest is also β_2 which captures the differential effect of shocks on migrant versus non-migrant households.

3.4 A Propensity Score Matching Technique

The OLS fixed effects model allows us to control for a wide range of individual covariates and also accounts for all time invariant unobservable characteristics at the country level through fixed effects estimation. Even though we focus on past exogenous shocks, as we show in Table 1 and Table 2, we found that certain individual characteristics are associated with a greater likelihood of being negatively affected by shocks. Indeed, we found that individuals who reported being negatively affected by shocks are more likely to live in rural areas and also more likely to have lower educational profiles. Although, we account for all these observable characteristics in our model, we also rely on a Propensity Score Matching (PSM) technique as a robustness check. The PSM technique allows us to predict the probability of being negatively affected by shocks subject to a set of observable characteristics. Using a logistic regression, we estimate the propensity score relying on equation (8) for women and men, separately.

$$Shock_i = \gamma_1 + \gamma_2 X_i + \varepsilon_i \quad (8)$$

The PSM technique allows us to pair treated individuals (those who witnessed shocks) with untreated individuals (those who did not witness shocks) who have similar values of the propensity score. First, we predict the propensity score based on the same set of covariates (X_i) presented in section 3.2. After the matching, the two groups of individuals are similar in terms of observable characteristics, apart from the treatment. Following Abadie and Imbens (2006), we rely on the nearest neighbor matching technique to predict the propensity score. We also rely on a matching technique without replacement, which means that an untreated unit can only be used once as a match. This is a well-adapted technique given the large sample size of untreated units relative to treated units (Caliendo & Kopeinig, 2008). Second, we combine our PSM technique with a standard OLS fixed effects model, based on the matched sample of treated and untreated units. Our sample therefore consists of individuals who reported being negatively affected by shocks and an equal number of individuals who were not affected by shocks but are very similar to the sample of treated units in terms of observable characteristics. We performed the matching at the individual level (for women and men, separately) and at the household level as presented in equation (9) and equation (10), respectively.

$$Y_i = \delta_1 + \delta_2 Migrant_i \times Shock_i + \delta_3 Shock_i + \delta_4 Migrant_i + \delta_5 X_i + \delta_6 Matched_i + \varepsilon_i \quad (9)$$

$$Y_h = \theta_1 + \theta_2 Migrant_h \times Shock_h + \theta_3 Shock_h + \theta_4 Migrant_h + \theta_5 X_h + \theta_6 Matched_h + \varepsilon_h \quad (10)$$

We also augment our standard OLS model by including a set of fixed effects for each pair of matched treated and untreated units $Matched_i$ and $Matched_h$. The inclusion of these fixed effects allows for a within comparison between treated and untreated observations with similar propensity score values. Moreover, these fixed effects allow us to control for all time invariant unobservable characteristics for each pair. The estimates from the PSM technique combined with the OLS fixed effects model are therefore purged out of any additional unobservable heterogeneity for a pair of matched individuals/households.

Another empirical challenge that we face is selection into migration. In Table A.2 and Table A.3 in the Online Appendix, we present descriptive statistics by migration status for women and men, respectively. As we show in Table A.2, migrant women are significantly younger than non-migrant women. They are also more likely to be married and to reside in rural areas relative to non-migrants. In terms of educational attainment, there seems to be a negative selection in terms of education for migrant relative to non-migrant women. Moreover, migrant women are more likely to be Muslim relative to non-migrants. Likewise, in Table A.3, we find significant differences between migrant and non-migrant men, consistent with the observed differences for women in the Online Appendix Table A.2.

As a robustness check, we deal with this additional layer of selection by performing a “double Propensity Score Matching technique.” Using the same set of covariates presented in section 3.2, we proceed by first predicting the probability of witnessing shocks. This first step leads to a matched sample of observations with similar values of the propensity score, i.e. similar likelihood of witnessing shocks based on observables. Based on the previously matched sample of individuals/households, we perform another PSM technique to deal with selection into migration. In this second step, our treatment is migration and we predict the propensity score in order to match migrants and non-migrants with similar values of the propensity score. Finally, based on the matched sample of migrants and non-migrants, we estimate our benchmark models relying on equation (9) and equation (10). In this setting, our model includes a set of fixed effects for each pair of migrant and non-migrant individuals in equation (9) and for each pair of migrant and non-migrant households, in equation (10). In the remainder of this paper, we refer to this technique as a “double Propensity Score Matching technique.” The advantage of this methodology is that it accounts for the selection on observables along two treatment dimensions: shocks and migration. Likewise, it allows for a within comparison between each pair of matched migrant and non-migrant and accounts for all time-invariant unobservable heterogeneity for each pair of matched observations.

Throughout our analysis, we rely on a standard OLS fixed effects as our benchmark model. This choice is driven by the need to maximize our sample size in order to examine the effect of shocks on various outcomes such as sectors of employment and

economic activities. Not only these outcomes are conditional on employment, which naturally limits our sample size, but the data is only available for a subset of employed individuals. For instance, the double PSM technique leads to approximately a 15 fold decrease in sample size for women and to a 12 fold decrease in men’s sample size.⁶ We therefore privileged to report all our results relying on the OLS fixed effects model. However, we believe the PSM results are highly informative and provide convincing evidence that neither one of these selection issues is driving our results.

4 Empirical Findings

4.1 The Effect on Participation and Employment

Relying on the EHCVM data, we estimate the effect of shocks on migrants in the receiving country and on non-migrants in the origin countries in the WAEMU. In Table 3, we estimate equation (1) relying on a standard OLS fixed effects model.⁷ These estimates allow us to disentangle the effect of negative shocks on labor market outcomes, as well as the effect of migration. Moreover, we assess whether shocks have a differential effect depending on the migration status of individuals. Our outcomes of interest include labor force participation, unemployment, and employment and we report the results for women and men, separately.

The results in Table 3 suggest that shocks have a negative effect on labor market outcomes for both women and men. Indeed, individuals who reported being negatively affected by shocks in the three years preceding the survey have lower labor force participation and employment. Moreover, past negative shocks are associated with greater unemployment for both women and men. In line with the stylized facts presented in section 2.3, we find that migration is associated with lower female labor force participation and lower employment. On the other hand, migration has a positive effect on male market outcomes. Indeed, we find that migration is associated with greater labor force participation and employment among migrant men, however, it is found to be associated with a decline in male unemployment. While migrant women have lower labor force participation and lower employment rates relative to non-migrant women, witnessing shocks is associated with an increase in migrant women’s labor force participation and employment. On the other hand, shocks do not have any differential effect for migrant men relative to non-migrants.

Relying on equations (2) to (5), we find that in the absence of shocks, non-migrant women have the highest employment rate (47%), while migrant women have the lowest employment rate (39%). On the other hand, the presence of shocks leads to a decline in female employment for non-migrant women (44%), while it leads to an increase in

⁶ See the number of observations in Table 3 and Table A.10 in the Online Appendix.

⁷ The results are also robust to using a probit model instead of a linear probability model as reported in Table A.4 in the Online Appendix and are very similar in terms of magnitude.

migrant women’s employment rate reaching 44%. While migrant women’s employment rate increases in the aftermath of shocks, it remains slightly lower than non-migrant women’s employment rate in the absence of shocks. However, shocks significantly narrowed the gap and led to an equalization in migrant and non-migrant women’s employment rates in the presence of shocks. As for men, we find that in the absence of shocks, migrant men’s employment rate stands at 64%, while non-migrant men’s employment rate is equal to 54%. Shocks lead to an almost equal decline, in absolute terms, in both migrant and non-migrant men’s employment rate. Therefore, even in the presence of shocks, migrant men tend to work more (62%) than non-migrants (51%).

Given the increase in migrant women’s labor force participation and employment in the aftermath of shocks, we investigate the effect of shocks on the gender gap in labor market outcomes. Table 4 focuses on intra-household differences in labor market outcomes by restricting our analysis to households composed of married couples of working age. Given that outcomes are defined as differences between the woman and her partner, a negative coefficient can be interpreted as an increase in the gender gap, while a positive coefficient is associated with a reduction in the gap. Our results highlight that shocks are associated with an increase, although small in magnitude, in the gender gap in labor force participation, employment, and unemployment. Likewise, migration leads to an increase in the gender gap, which is not surprising given the fact that women tend to migrate for marriage. The increase in the gender gap associated with migration is large: migration is associated with approximately 20 percentage points increase in the gender gap in labor force participation and employment. However, we find that shocks reduce the gender gap among migrant women. Indeed, we find that shocks are associated with 10 percentage points decline in the gender gap for migrant households.

4.2 The Effect on Economic Sectors and Activities

Table 5 features differences in terms of sectors of employment and economic activities between migrants and non-migrants, by gender. We find important differences between migrant and non-migrant individuals that apply to both women (Panel A) and men (Panel B). Non-migrants are more likely to be employed in the public sector relative to migrants, while migrant individuals are almost exclusively employed in the private sector. In terms of economic activities, we find that both migrant women and men are more likely to be employed in agriculture, and wholesale and retail trade relative to non-migrants. Migrant women also have a greater likelihood of being employed in hotels and restauration compared to non-migrant women.

In this section, we investigate whether shocks have a differential effect on sectors of employment and economic activities for migrants and non-migrants. In Table 6,

conditional on employment, we estimate the effect of shocks on the probability of being employed in the public sector, private sector or domestic work. Shocks and migration are associated with a greater probability of being employed in the private sector as opposed to being employed in the public sector, for both women and men. Although shocks are associated with labor reallocation from the public to the private sector among non-migrants in WAEMU countries, we find evidence that the public sector in Ivory Coast in the aftermath of shocks absorbs migrant labor from the private sector. Moreover, we find a small increase in women’s engagement in domestic work among migrant women who are negatively affected by shocks.

Exploring the effect of shocks on economic activities in Table 7, we find a positive association between the incidence of shocks and employment in agriculture and a negative association between shocks and employment in any other economic activity, for both women and men. Given that shocks predominantly consist of climate shocks, this means that being negatively affected by past shocks did not lead to a reallocation of labor away from agriculture, possibly because of a lack of opportunities in other sectors. While migrant women are found to be more likely to work in wholesale and retail trade and hotels and restauration, shocks seem to be associated with a decline in migrant women’s engagement in both economic activities and an increase in the probability of working in personal services and other activities. On the other hand, although migrant men are found to be significantly more likely to work in agriculture and wholesale and retail trade, we find that migrant men who are negatively affected by shocks are also more likely to work in personal services and other activities.

4.3 Heterogeneity Analysis

In this section, we perform several heterogeneity analyses. First, we disentangle the effect of shocks related to climate from those related to armed conflict and violence in Table A.5 in the Online Appendix. Our model includes a dummy variable for individuals who reported being negatively affected by armed conflict/violence/insecurity, a dummy variable for individuals who reported being negatively affected by climate shocks such as droughts/irregular rain, floods, fires, and landslides, the interaction term between the two, an interaction term between migration and violence, an interaction term between migration and climate shocks, and a triple interaction between migration, violence, and climate shocks.

While climate shocks are associated with a decline in labor force participation and employment for both women and men, we find that violence has a detrimental effect on women’s labor market outcomes only. On the other hand, while migration is associated with a decline in women’s participation and employment, we consistently find that climate shocks lead to an increase in female participation and employment and to a decline in unemployment among migrant women. However, we find that

shocks related to armed conflict do not exert any differential effect on migrant women although they lead to an increase in migrant men’s participation. When migrants face both climate and violence related shocks, women’s labor force participation and employment decline, while they increase among migrant men. These findings suggest that migrant women bear the negative consequences of climate shocks by increasing their labor force participation, while the responsibility falls upon men when facing shocks related to armed conflict and violence. These findings relate to [Berrebi and Ostwald \(2016\)](#) who, in a large cross-country analysis covering almost 30 years, find that terrorist attacks lead to a decrease in female labor force participation and to an increase in the gender gap between men and women.

Second, we investigate the heterogenous effects by household wealth in [Table A.6](#) in the Online Appendix. We compute a wealth index using a Principal Component Analysis (PCA). The wealth score is computed relying on household ownership of a number of durable goods including: air conditioner, water heater, and fan. Our wealth index is also computed based on indicators reflecting the overall quality of the dwelling unit which include a dummy for external dwelling walls being made of cement/concrete/cut stones or fired bricks, a dummy for ceiling being made of concrete slab, tile or ceiling sheets, a dummy for floor covering being made of tiles/marble or cement/concrete, a dummy variable for water access, and a dummy variable for electricity access. In [Table A.6](#) in the Online Appendix, we split our sample based on the median value of the wealth score. In Panel A, we report results for individuals with above median wealth score, while Panel B reports results for individuals with below median wealth score. We find that migration consistently leads to a decline in women’s labor market outcomes, regardless of whether the women belong to richer or poorer households. However, shocks negatively affect the labor market outcomes of women who belong to the wealthiest households by reducing participation and employment and increasing unemployment, while they do not have any impact on women who belong to households with below median wealth score. The increase in migrant women’s labor force participation and employment and the decline in unemployment following shocks is therefore driven by women who belong to wealthier households. This is likely due to the differential effects of shocks on women’s labor market outcomes based on their wealth score, with women in lower wealth quintiles having no choice but to work, while women in upper wealth quintiles may quit work when the benefits from work are not matching their reservation wages due to shocks leading to lower productivity.

5 Robustness Checks

As presented in [section 3.4](#), we also rely on a PSM technique in order to match individuals with similar propensity of witnessing shocks. We perform our matching for women and men, separately, relying on a nearest neighbor estimator. In order to pre-

dict the propensity score, we rely on logistic regressions as reported in Table A.7 in the Online Appendix. We find that having lower levels of educational attainment are associated with a greater likelihood of being negatively affected by shocks, for both women and men. Likewise, rural residency is associated with higher probability of witnessing shocks. We also control for age, marital status, religion, and countries of origin when predicting the propensity score.

Before presenting the results from the PSM technique, we check for covariate balance before and after matching. In Table A.8 and Table A.9 in the Online Appendix, we report descriptive statistics on all covariates included in our regressions for treated and untreated units, before and after matching. We also check whether the differences between treated and untreated observations are statistically significant before and after we perform the matching. For both women and men, we find that the matching led to a significant reduction in differences between treated and untreated units after the matching. While women and men who witnessed shocks and those who did not were significantly different along all dimensions, we find that the matching successfully achieved covariate balance in terms of education and individual characteristics. Although some small differences still remain, in particular in terms of religion and countries of origin, the gaps between treated and untreated after the matching are consistently smaller than before the matching. Moreover, we additionally control for all these covariates in our regressions after the matching.

We report the results relying on the PSM technique in Table 8 and Table 9. Table 8 presents the effect of shocks on labor force participation, employment, and unemployment, while Table 9 examines the effect on intra-household differences in labor market outcomes. Our regressions now additionally include pair fixed effects to allow for a within comparison for each pair of matched individuals/households. Consistent with our benchmark results, we find that shocks lead to a decline in both female and male labor force participation and employment, and to an increase in unemployment. Migration has a positive effect on men’s labor market outcomes, while it leads to a decline in women’s participation and employment. We also consistently find that shocks are associated with an increase in women’s labor force participation and employment among migrant women. Our results in Table 9 also show that shocks are associated with a decline in the gender gap in labor force participation and employment among migrant women.

We also report results relying on a double PSM technique in which we first match individuals who have similar propensity of witnessing shocks. As presented in section 3.4, we predict the probability of migration, based on the previously matched sample, and perform an additional matching based on individuals’ predicted propensity of migration. Our regressions also include pair fixed effects for each pair of matched migrant and non-migrant. We report our results in Table A10 and Table A.11 in the Online Appendix. Our findings are fully in line with the benchmark results presented

in section 4.1. The magnitude of the estimated coefficient from the PSM and double PSM technique are larger than the standard OLS fixed effects model. This suggests that not accounting for selection issues can be associated with a downward bias in our main results, likely due to the negative selection of migrants relative to non-migrants. The robustness of our results to using a PSM and a double PSM technique bolsters our confidence that selection issues are not driving our results.

Finally, as an additional robustness check, in Table A.12 and Table A.13 in the Online Appendix, our sample additionally includes nationals from Ivory Coast, whereas our benchmark results only included migrant population in Ivory Coast. Our regressions therefore include an additional dummy for Ivory Coast among our countries of origin fixed effects. Our results are robust to this check and consistently show that shocks increase migrant women’s participation and employment, as presented in Table A.12. Table A.13 also consistently shows that shocks are associated with a decline in the gender gap in labor force participation and employment in migrant households.

6 Concluding Remarks

Households in West Africa are exposed to a myriad of shocks including climate shocks such as droughts, floods, fires, and landslides. The effect of these climate shocks can be exacerbated by other shocks such as exposure to violence and armed conflict. In this paper, we study the effect of these shocks on migrant and non-migrant households in West Africa. We adopt a gender perspective and examine how migrant and non-migrant women’s labor force participation, employment, and unemployment respond to shocks.

Combining data on both migrant receiving country (Ivory Coast) and migrant sending countries (Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo), we are able to compare migrants and non-migrants from the same origin countries. Our analysis relies on pooled cross-sectional data from the EHCVM surveys administered across all 8 countries of the WAEMU. We find evidence of lower female labor force participation rates among migrant women relative to non-migrants, as female migration in West Africa is predominantly motivated by marriage. However, our results indicate an increase in labor force participation and employment among migrant women negatively affected by shocks. Likewise, our results show a narrowing of the gender gap in labor force participation and employment in migrant households negatively affected by shocks.

Our findings relate to the literature on how female labor supply responds to shocks such as political, economic, demographic, and technological shocks. Our paper provides evidence on how female labor force participation responds to climate and political shocks in West Africa and carries important implications that go beyond our case study. Indeed, female marriage migration—although prevalent in West Africa—afflicts

other developing countries such as India and Malaysia. Our analysis shows that in such contexts where female labor is considered as “reserve labor,” shocks might provide leeway to contest long-standing social norms on the role of women in society and thus lead to an increase in female labor force participation rates. Our paper likewise relates to the literature on the risk management strategies employed by poor households to face adverse shocks, by highlighting the understudied issue of women’s engagement in the labor market when households are affected by covariate shocks.

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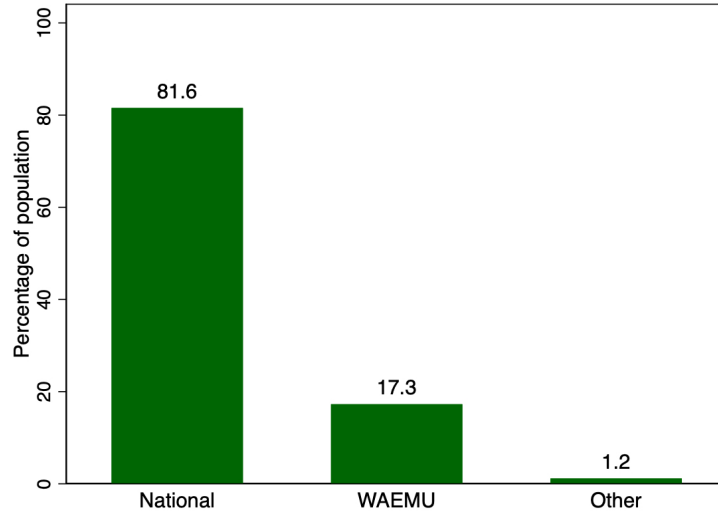
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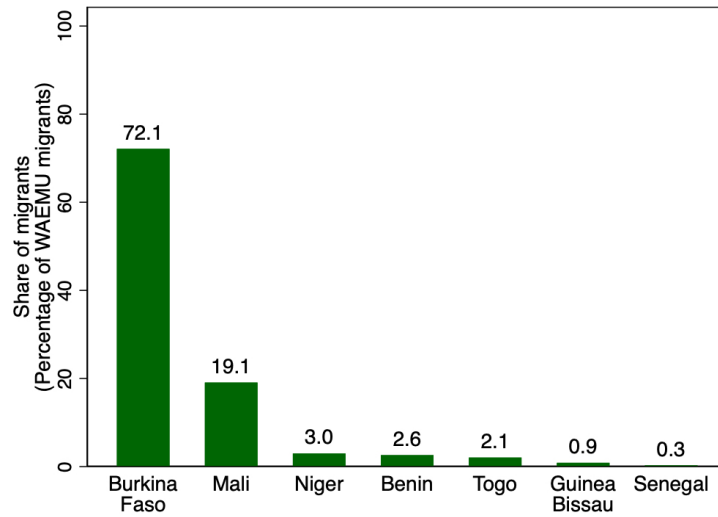
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(a) Total population



(b) Nationality breakdown for WAEMU

Figure 1: Population distribution in Ivory Coast

Notes. This figure relies on data from the EHCVM in Ivory Coast conducted in two waves in 2018 and 2019. Panel A presents the total population distribution, while Panel B presents the nationality breakdown for WAEMU immigrants in Ivory Coast.

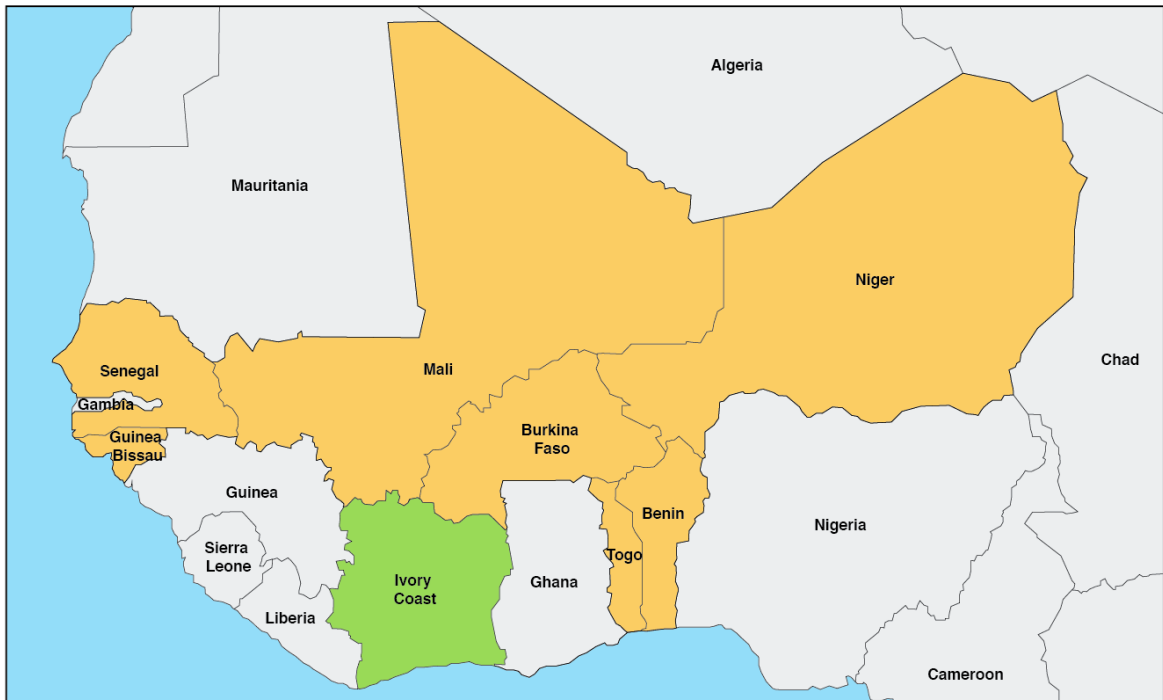
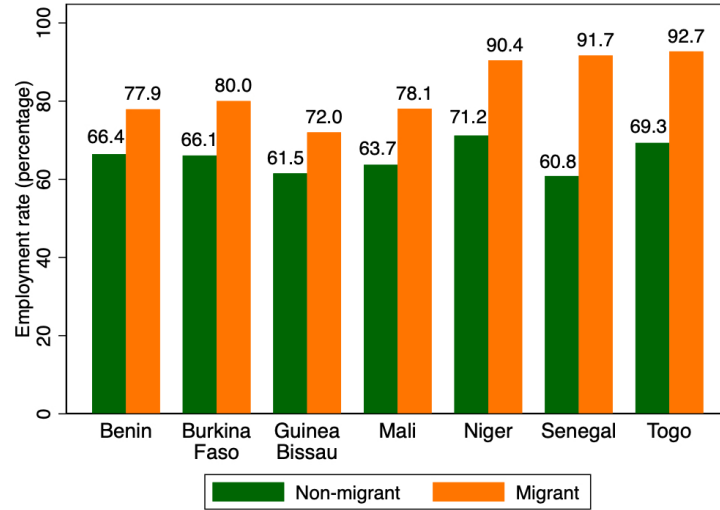
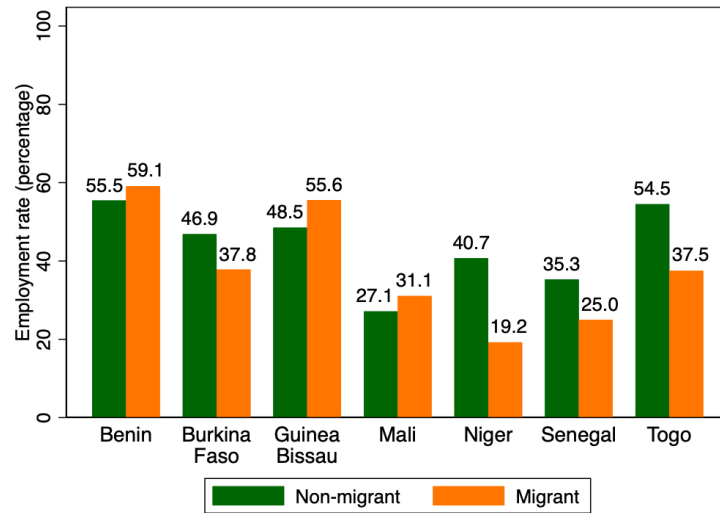


Figure 2: Countries of origin of WAEMU migrants in Ivory Coast

Notes. This map presents the countries of origin of West African Economic and Monetary Union (WAEMU) migrants in Ivory Coast. Ivory Coast is presented in green, while the countries of origin of WAEMU migrants are presented in orange. Data on the origin countries of WAEMU migrants in Ivory Coast comes from the *Enquête Harmonisée sur les Conditions de Vie des Ménages (EHCVM)* conducted in two waves in 2018 and 2019.



(a) Male employment rates



(b) Female employment rates

Figure 3: Employment rates among migrant and non-migrant households, by gender

Notes. This figure relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data from Ivory Coast to compute WAEMU immigrant employment rates, while we rely on data from Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo to compute non-migrant employment rates. The analysis is restricted to working age population (15 to 64 years old). Individuals are defined as employed if they worked at least one hour in the week preceding the survey or had a job but did not work in the week preceding the survey due to being on vacation, leave, sick leave, etc. Employment includes wage work, self-employed and unpaid family work.

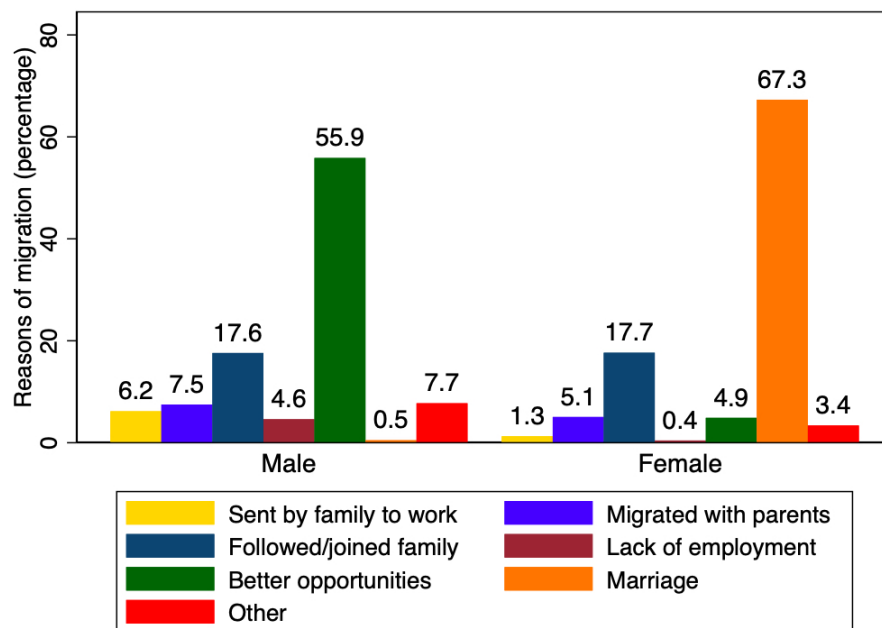
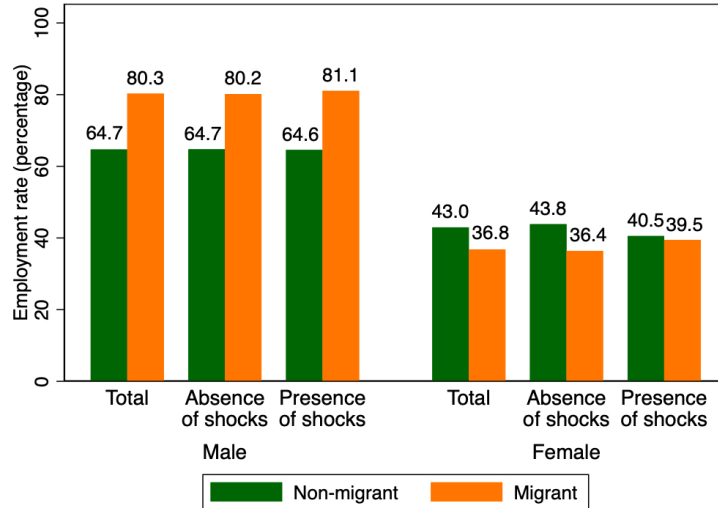
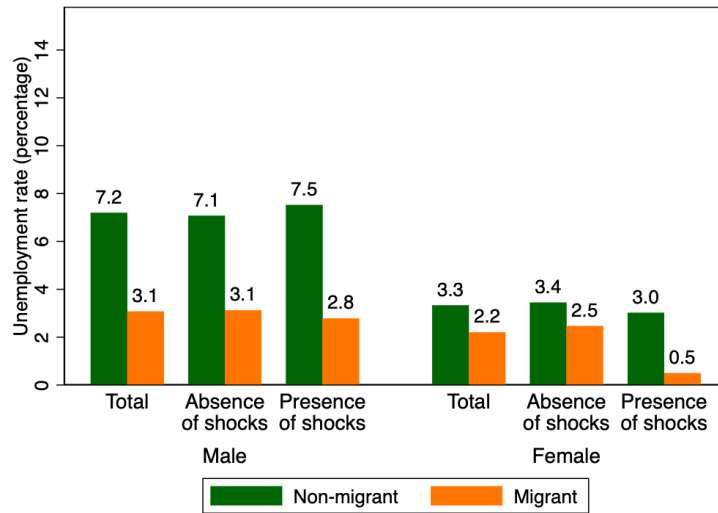


Figure 4: Reasons of migration by gender

Notes. This figure relies on data from the EHCVM survey in Ivory Coast conducted in two waves in 2018 and 2019. Individuals were asked about the reasons they choose to live in this locality as opposed to their previous location of residence. Focusing on the WAEMU immigrant population in Ivory Coast, we identify the reasons of migration. Other reasons include assignment, lack of land, school, divorce, loss of spouse, illness of a household member, other family problems, armed conflicts, political or economic instability, and natural disasters.



(a) Employment rates



(b) Unemployment rates

Figure 5: Employment and unemployment rates among migrant and non-migrant households, by exposure to shocks and gender

Notes. This figure relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data from Ivory Coast to compute WAEMU immigrant employment and unemployment rates, while we rely on data from Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo to compute non-migrant employment and unemployment rates. Rates are computed by gender, migration status, and exposure to shocks. Households are exposed to shocks if they reported being negatively affected by a given shock in the three years preceding the survey. We consider shocks related to violence: armed conflict/violence/insecurity, and climate shocks such as droughts/irregular rain, floods, fires, and landslides. The analysis is restricted to working age population (15 to 64 years old). Individuals are defined as employed if they worked at least one hour in the week preceding the survey or had a job but did not work in the week preceding the survey due to being on vacation, leave, sick leave, etc. Unemployed individuals are defined as those who engage in subsistence economic activities (without remuneration) but are actively searching for employment or as those who do not engage in any activity and are also actively searching for employment. We also define as unemployed those who are not actively searching for a job but are waiting for a response on a job application and are immediately available to work.

Table 1: Descriptive statistics on the sample of women, by exposure to shocks

	Shocks		No shocks		Difference
	Mean	St. Dev.	Mean	St. Dev.	
<i>Individual characteristics</i>					
Age	34.609	12.651	34.921	12.580	-0.312***
Married	0.795	0.404	0.726	0.446	0.069***
Rural	0.761	0.426	0.526	0.499	0.235***
Migrant	0.017	0.130	0.041	0.197	-0.023***
<i>Education</i>					
No education	0.801	0.399	0.650	0.477	0.151***
Primary or less	0.128	0.334	0.188	0.391	-0.060***
Secondary	0.056	0.230	0.109	0.311	-0.052***
Upper secondary	0.011	0.105	0.035	0.184	-0.024***
Post-secondary and above	0.003	0.057	0.018	0.134	-0.015***
<i>Religion</i>					
Muslim	0.726	0.446	0.670	0.470	0.057***
Christian	0.174	0.379	0.240	0.427	-0.066***
Animist	0.078	0.268	0.063	0.244	0.014***
Other religion	0.001	0.036	0.002	0.049	-0.001***
No religion	0.021	0.143	0.025	0.155	-0.004***
<i>Country</i>					
Benin	0.125	0.331	0.145	0.352	-0.019***
Burkina Faso	0.263	0.440	0.152	0.359	0.111***
Guinea-Bissau	0.096	0.295	0.144	0.351	-0.048***
Mali	0.245	0.430	0.125	0.331	0.120***
Niger	0.093	0.290	0.073	0.261	0.019***
Senegal	0.120	0.325	0.258	0.437	-0.138***
Togo	0.058	0.233	0.103	0.304	-0.046***
Observations	18,146		47,538		

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Descriptive statistics are reported by exposure to shocks. The analysis is restricted to working age women (15 to 64 years old). Households are exposed to shocks if they reported being negatively affected by a given shock in the three years preceding the survey. We consider shocks related to violence: armed conflict/violence/insecurity, and climate shocks such as droughts/irregular rain, floods, fires, and landslides. The last column reports the difference in means between individuals exposed to shocks and those that are not, as well as a t-test of whether the difference in means between the two groups is significant.

Table 2: Descriptive statistics on the sample of men, by exposure to shocks

	Shocks		No shocks		Difference
	Mean	St. Dev.	Mean	St. Dev.	
<i>Individual characteristics</i>					
Age	35.757	13.708	35.875	12.872	-0.117
Married	0.667	0.471	0.633	0.482	0.035***
Rural	0.755	0.430	0.513	0.500	0.242***
Migrant	0.024	0.152	0.057	0.232	-0.033***
<i>Education</i>					
No education	0.676	0.468	0.493	0.500	0.183***
Primary or less	0.195	0.396	0.230	0.421	-0.035***
Secondary	0.091	0.288	0.160	0.366	-0.069***
Upper secondary	0.026	0.159	0.065	0.246	-0.039***
Post-secondary and above	0.012	0.110	0.053	0.223	-0.040***
<i>Religion</i>					
Muslim	0.741	0.438	0.678	0.467	0.064***
Christian	0.159	0.365	0.229	0.420	-0.070***
Animist	0.077	0.266	0.063	0.243	0.013***
Other religion	0.002	0.044	0.002	0.047	0.000
No religion	0.021	0.145	0.028	0.166	-0.007***
<i>Country</i>					
Benin	0.123	0.329	0.145	0.353	-0.022***
Burkina Faso	0.257	0.437	0.163	0.369	0.093***
Guinea-Bissau	0.092	0.289	0.140	0.347	-0.047***
Mali	0.256	0.436	0.132	0.338	0.124***
Niger	0.104	0.305	0.081	0.273	0.023***
Senegal	0.113	0.317	0.240	0.427	-0.127***
Togo	0.054	0.227	0.099	0.299	-0.044***
Observations	15,165		39,423		

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Descriptive statistics are reported by exposure to shocks. The analysis is restricted to working age men (15 to 64 years old). Households are exposed to shocks if they reported being negatively affected by a given shock in the three years preceding the survey. We consider shocks related to violence: armed conflict/violence/insecurity, and climate shocks such as droughts/irregular rain, floods, fires, and landslides. The last column reports the difference in means between individuals exposed to shocks and those that are not, as well as a t-test of whether the difference in means between the two groups is significant.

Table 3: The effect of shocks on labor force participation, employment, and unemployment

	Panel A: Sample of women			Panel B: Sample of men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force Participation	Emp.	Unemp.	Labor Force Participation	Emp.	Unemp.
Migrant × Shock	0.062** [0.031]	0.076** [0.031]	-0.014*** [0.004]	0.007 [0.018]	0.010 [0.018]	-0.004 [0.005]
Migrant	-0.089*** [0.012]	-0.079*** [0.012]	-0.009*** [0.003]	0.080*** [0.007]	0.102*** [0.007]	-0.022*** [0.002]
Shock	-0.020*** [0.004]	-0.024*** [0.004]	0.004*** [0.001]	-0.030*** [0.004]	-0.037*** [0.004]	0.007*** [0.002]
Constant	0.639*** [0.016]	0.468*** [0.018]	0.172*** [0.012]	0.650*** [0.010]	0.542*** [0.011]	0.109*** [0.007]
Observations	65,684	65,684	65,684	54,588	54,588	54,588
R-squared	0.097	0.093	0.030	0.177	0.198	0.029
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Dependent variable mean	0.504	0.484	0.020	0.795	0.769	0.026

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table 4: The effect of shocks on intra-household differences in labor market outcomes

	(1)	(2)	(3)
	Labor Force Participation	Employment	Unemployment
Migrant \times Shock	0.103** [0.045]	0.099** [0.045]	0.005 [0.007]
Migrant	-0.214*** [0.018]	-0.198*** [0.018]	-0.016*** [0.004]
Shock	-0.026*** [0.008]	-0.022*** [0.008]	-0.004* [0.002]
Observations	21,752	21,752	21,752
R-squared	0.109	0.105	0.008
Household controls	YES	YES	YES
Country FE	YES	YES	YES
Dependent variable mean	-0.405	-0.414	0.009

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The unit of analysis is the household and the analysis is restricted to married couples of working age. The dependent variables are defined as the difference in dummy variable indicators for labor force participation, employment, and unemployment between the woman and her spouse in a given household. For labor force participation, the dependent variable takes the value -1 if the woman is not participating in the labor market, while the man is participating; it takes the value 0 if both are participating or both are not participating; and it takes the value 1 if the woman is participating, while the man is not. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include the following household controls: age of the woman and her spouse, a dummy for rural residence, the difference in the highest level of educational attainment between the woman and her spouse (no education, primary or less, secondary, upper secondary, post-secondary and above), and dummies for the religion of the household head (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects for the household head: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table 5: Job characteristics among migrants and non-migrants, by gender

Panel A: Sample of women					
	Migrant		Non-migrant		
	Mean	St. Dev.	Mean	St. Dev.	Difference
<i>Sector of employment</i>					
Public	0.000	0.000	0.035	0.184	-0.035***
Private	0.984	0.126	0.945	0.228	0.039***
Domestic work	0.016	0.126	0.020	0.139	-0.004
<i>Economic activity</i>					
Agriculture	0.483	0.500	0.375	0.484	0.108***
Manufacturing	0.098	0.297	0.159	0.366	-0.061***
Wholesale and retail trade	0.289	0.454	0.243	0.429	0.046***
Hotels and restauration	0.063	0.244	0.044	0.206	0.019***
Personal services workers	0.041	0.200	0.092	0.289	-0.050***
Other	0.025	0.157	0.087	0.281	-0.061***
Observations	868		30,936		
Panel B: Sample of men					
<i>Sector of employment</i>					
Public	0.003	0.052	0.070	0.255	-0.067***
Private	0.990	0.101	0.921	0.269	0.068***
Domestic work	0.008	0.087	0.008	0.091	-0.001
<i>Economic activity</i>					
Agriculture	0.634	0.482	0.463	0.499	0.172***
Manufacturing	0.050	0.217	0.072	0.258	-0.022***
Wholesale and retail trade	0.174	0.380	0.109	0.311	0.066***
Hotels and restauration	0.009	0.094	0.006	0.080	0.002
Personal services workers	0.030	0.169	0.103	0.304	-0.073***
Other	0.103	0.304	0.248	0.432	-0.145***
Observations	2,231		39,753		

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The analysis is restricted to working age women in Panel A and to working age men in Panel B. The table reports descriptive statistics on job characteristics for migrant and non-migrants. Migrants refer to WAEMU immigrants in Ivory Coast, while non-migrants refer to WAEMU nationals surveyed in their respective countries. Job characteristics include sectors of employment, economic activities, as wages and hours of work.

Table 6: The effect of shocks on sector of employment

	Panel A: Sample of women			Panel B: Sample of men		
	(1) Public	(2) Private	(3) Domestic	(4) Public	(5) Private	(6) Domestic
Migrant \times Shock	0.011*** [0.002]	-0.026*** [0.010]	0.016* [0.009]	0.015*** [0.004]	-0.011* [0.006]	-0.005 [0.004]
Migrant	-0.016*** [0.002]	0.024*** [0.004]	-0.008** [0.003]	-0.032*** [0.002]	0.031*** [0.003]	0.001 [0.002]
Shock	-0.005*** [0.001]	0.011*** [0.002]	-0.006*** [0.001]	-0.011*** [0.002]	0.012*** [0.002]	-0.001 [0.001]
Observations	43,342	43,342	43,342	48,498	48,498	48,498
R-squared	0.231	0.155	0.054	0.243	0.214	0.007
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Dependent variable mean	0.025	0.959	0.016	0.058	0.934	0.008

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for being employed in the public sector, private sector or in domestic work. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table 7: The effect of shocks on economic activity

Panel A: Sample of women						
	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture	Manufacturing	Wholesale and retail trade	Hotels and restauration	Personal services workers	Other
Migrant \times Shock	0.041 [0.030]	-0.042*** [0.011]	-0.032 [0.025]	-0.019* [0.011]	0.035*** [0.013]	0.017** [0.008]
Migrant	-0.012 [0.014]	-0.023*** [0.009]	0.074*** [0.012]	0.023*** [0.007]	-0.034*** [0.006]	-0.029*** [0.005]
Shock	0.113*** [0.005]	-0.017*** [0.004]	-0.050*** [0.004]	-0.009*** [0.002]	-0.020*** [0.002]	-0.018*** [0.002]
Observations	43,339	43,339	43,339	43,339	43,339	43,339
R-squared	0.377	0.039	0.115	0.033	0.062	0.237
Dependent variable mean	0.513	0.125	0.191	0.036	0.071	0.066
Panel B: Sample of men						
Migrant \times Shock	-0.014 [0.022]	0.006 [0.011]	-0.047*** [0.018]	0.002 [0.005]	0.024*** [0.008]	0.029** [0.014]
Migrant	0.050*** [0.010]	-0.002 [0.005]	0.070*** [0.009]	0.002 [0.002]	-0.052*** [0.005]	-0.067*** [0.007]
Shock	0.136*** [0.005]	-0.016*** [0.002]	-0.027*** [0.003]	-0.002*** [0.001]	-0.030*** [0.003]	-0.061*** [0.004]
Observations	48,498	48,498	48,498	48,498	48,498	48,498
R-squared	0.371	0.041	0.044	0.006	0.055	0.198
Dependent variable mean	0.522	0.065	0.102	0.006	0.090	0.215
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in Panel A and to working age men in Panel B. The dependent variables are dummy variable indicators for being employed in agriculture, manufacturing, wholesale and retail trade, hotels and restauration, personal services workers, or other economic activities. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table 8: Robustness checks using PSM.
The effect of shocks on labor force participation, employment, and unemployment

	Panel A: Sample of women			Panel B: Sample of men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force Participation	Emp.	Unemp.	Labor Force Participation	Emp.	Unemp.
Migrant \times Shock	0.094** [0.043]	0.097** [0.043]	-0.002 [0.008]	0.015 [0.025]	0.018 [0.025]	-0.003 [0.008]
Migrant	-0.118*** [0.017]	-0.102*** [0.017]	-0.016*** [0.005]	0.065*** [0.012]	0.083*** [0.013]	-0.018*** [0.005]
Shock	-0.038*** [0.005]	-0.042*** [0.005]	0.004*** [0.001]	-0.036*** [0.005]	-0.045*** [0.005]	0.009*** [0.002]
Observations	36,284	36,284	36,284	30,328	30,328	30,328
R-squared	0.555	0.553	0.507	0.627	0.637	0.516
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Individual pair FE	YES	YES	YES	YES	YES	YES
Dependent variable mean	0.470	0.454	0.016	0.779	0.757	0.022

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on Propensity Score Matching followed by a standard OLS fixed effects model. Using a nearest neighbor matching technique, individuals are matched based on their propensity to witness shocks. To predict the propensity score, the PSM technique relies on the same set of regressors included in the benchmark model at the individual level. Following PSM, results are reported using a standard OLS fixed effects model that includes a fixed effect for each pair of matched treated and untreated unit. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table 9: Robustness checks using PSM.
The effect of shocks on intra-household differences in labor market outcomes

	(1)	(2)	(3)
	Labor Force Participation	Employment	Unemployment
Migrant \times Shock	0.153** [0.062]	0.151** [0.063]	0.001 [0.013]
Migrant	-0.225*** [0.030]	-0.215*** [0.030]	-0.011 [0.007]
Shock	-0.027*** [0.010]	-0.024** [0.010]	-0.003 [0.003]
Observations	12,180	12,180	12,180
R-squared	0.561	0.560	0.506
Household controls	YES	YES	YES
Country FE	YES	YES	YES
Household pair FE	YES	YES	YES
Dependent variable mean	-0.450	-0.458	0.007

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on Propensity Score Matching followed by a standard OLS fixed effects model. The unit of analysis is the household. Using a nearest neighbor matching technique, households are matched based on their propensity to witness shocks. To predict the propensity score, the PSM technique relies on the same set of regressors included in the benchmark model at the household level. Following PSM, results are reported using a standard OLS fixed effects model that includes a fixed effect for each pair of matched treated and untreated unit. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The dependent variables are defined as the difference in dummy variable indicators for labor force participation, employment, and unemployment between the woman and her spouse in a given household. For labor force participation, the dependent variables takes the value -1 if the woman is not participating in the labor market, while the man is participating; it takes the value 0 if both are participating or both are not participating; and it takes the value 1 if the woman is participating, while the man is not. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include the following household controls: age of the woman and her spouse, a dummy for rural residence, the difference in the highest level of educational attainment between the woman and her spouse (no education, primary or less, secondary, upper secondary, post-secondary and above), and dummies for the religion of the household head (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects for the household head: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

A Online Appendix

Table A.1: Incidence of conflict and climate shocks, by country

	Drought	Flood	Fire	Landslide	Conflict	Any shock
	Mean (St. Dev.)	Mean (St. Dev.)	Mean (St. Dev.)	Mean (St. Dev.)	Mean (St. Dev.)	Mean (St. Dev.)
Benin (N=19,587)	0.126 (0.332)	0.109 (0.312)	0.014 (0.116)	0.005 (0.069)	0.009 (0.093)	0.241 (0.428)
Burkina Faso (N=22,506)	0.357 (0.479)	0.073 (0.260)	0.007 (0.084)	0.027 (0.161)	0.000 (0.009)	0.420 (0.494)
Guinea-Bissau (N=20,912)	0.100 (0.299)	0.065 (0.247)	0.045 (0.208)	0.011 (0.105)	0.005 (0.072)	0.194 (0.395)
Ivory Coast (N=5,178)	0.107 (0.309)	0.026 (0.159)	0.007 (0.085)	0.011 (0.103)	0.002 (0.046)	0.138 (0.344)
Mali (N=20,795)	0.259 (0.438)	0.107 (0.309)	0.010 (0.100)	0.151 (0.358)	0.002 (0.045)	0.423 (0.494)
Niger (N=11,091)	0.219 (0.414)	0.084 (0.278)	0.019 (0.138)	0.023 (0.151)	0.004 (0.065)	0.314 (0.464)
Senegal (N=30,804)	0.087 (0.282)	0.045 (0.206)	0.023 (0.149)	0.003 (0.055)	0.002 (0.041)	0.144 (0.351)
Togo (N=13,091)	0.104 (0.306)	0.050 (0.218)	0.017 (0.128)	0.010 (0.098)	0.001 (0.023)	0.169 (0.375)

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The table reports the incidence of conflict and climate shocks, by country. Ivory Coast refers to the immigrant population from the WAEMU countries, while all the other countries refer to the native population in the respective country. The sample corresponds to the estimation sample in the benchmark model.

Table A.2: Descriptive statistics on the sample of women, by migration status

	Migrants		Non-migrants		Difference
	Mean	St. Dev.	Mean	St. Dev.	
<i>Individual characteristics</i>					
Age	31.804	11.230	34.942	12.633	-3.138***
Married	0.834	0.372	0.742	0.438	0.092***
Rural	0.651	0.477	0.589	0.492	0.062***
Shocks	0.140	0.347	0.281	0.450	-0.141***
<i>Education</i>					
No education	0.846	0.361	0.686	0.464	0.160***
Primary or less	0.099	0.299	0.174	0.379	-0.075***
Secondary	0.045	0.206	0.096	0.294	-0.051***
Upper secondary	0.010	0.099	0.029	0.168	-0.019***
Post-secondary and above	0.000	0.021	0.015	0.120	-0.014***
<i>Religion</i>					
Muslim	0.775	0.418	0.682	0.466	0.093***
Christian	0.199	0.400	0.222	0.416	-0.023**
Animist	0.010	0.101	0.069	0.254	-0.059***
Other religion	0.001	0.037	0.002	0.046	-0.001
No religion	0.014	0.119	0.024	0.153	-0.010***
<i>Country</i>					
Benin	0.027	0.161	0.143	0.350	-0.117***
Burkina Faso	0.718	0.450	0.164	0.370	0.555***
Guinea-Bissau	0.012	0.107	0.135	0.342	-0.123***
Mali	0.199	0.400	0.157	0.364	0.042***
Niger	0.022	0.146	0.081	0.273	-0.059***
Senegal	0.003	0.056	0.227	0.419	-0.224***
Togo	0.019	0.137	0.093	0.291	-0.074***
Observations	2,243		63,441		

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Descriptive statistics are reported by migration status. The analysis is restricted to working age women (15 to 64 years old). The last column reports the difference in means between migrants and non-migrants, as well as a t-test of whether the difference in means between the two groups is significant.

Table A.3: Descriptive statistics on the sample of men, by migration status

	Migrants		Non-migrants		Difference
	Mean	St. Dev.	Mean	St. Dev.	
<i>Individual characteristics</i>					
Age	35.169	12.196	35.876	13.152	-0.707***
Married	0.645	0.479	0.642	0.479	0.003
Rural	0.666	0.472	0.576	0.494	0.090***
Shocks	0.139	0.346	0.285	0.451	-0.146***
<i>Education</i>					
No education	0.713	0.452	0.536	0.499	0.178***
Primary or less	0.177	0.382	0.222	0.416	-0.045***
Secondary	0.084	0.278	0.144	0.351	-0.059***
Upper secondary	0.021	0.143	0.056	0.229	-0.035***
Post-secondary and above	0.005	0.068	0.043	0.203	-0.039***
<i>Religion</i>					
Muslim	0.756	0.429	0.692	0.462	0.064***
Christian	0.210	0.407	0.209	0.407	0.001
Animist	0.012	0.107	0.070	0.255	-0.058***
Other religion	0.001	0.034	0.002	0.047	-0.001
No religion	0.021	0.144	0.027	0.161	-0.006*
<i>Country</i>					
Benin	0.025	0.157	0.145	0.352	-0.120***
Burkina Faso	0.723	0.447	0.162	0.369	0.561***
Guinea-Bissau	0.008	0.092	0.132	0.339	-0.124***
Mali	0.177	0.382	0.166	0.372	0.011
Niger	0.042	0.200	0.090	0.286	-0.048***
Senegal	0.005	0.068	0.215	0.411	-0.210***
Togo	0.020	0.139	0.090	0.286	-0.070***
Observations	2,605		51,983		

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Descriptive statistics are reported by migration status. The analysis is restricted to working age men (15 to 64 years old). The last column reports the difference in means between migrants and non-migrants, as well as a t-test of whether the difference in means between the two groups is significant.

Table A.4: The effect of shocks on labor force participation, employment, and unemployment using a probit model

	Panel A: Sample of women			Panel B: Sample of men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force Participation	Emp.	Unemp.	Labor Force Participation	Emp.	Unemp.
Migrant \times Shock	0.062** (0.030)	0.077** (0.030)	-0.030** (0.015)	0.002 (0.022)	0.005 (0.023)	-0.006 (0.016)
Migrant	-0.086*** (0.012)	-0.077*** (0.012)	-0.007** (0.004)	0.088*** (0.009)	0.114*** (0.009)	-0.034*** (0.006)
Shock	-0.020*** (0.004)	-0.024*** (0.004)	0.005*** (0.001)	-0.026*** (0.004)	-0.033*** (0.004)	0.007*** (0.002)
Observations	65,684	65,684	65,684	54,588	54,588	54,588
R-squared	0.097	0.093	0.030	0.177	0.198	0.029
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Dependent variable mean	0.504	0.484	0.020	0.795	0.769	0.026

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in brackets.

Notes: Marginal effects are reported using a probit model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table A.5: Investigating the effect of violence versus climate shocks on women's labor market outcomes

	Panel A: Sample of women			Panel B: Sample of men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force Participation	Emp.	Unemp.	Labor Force Participation	Emp.	Unemp.
Migrant × Climate	0.068** [0.032]	0.082*** [0.032]	-0.013*** [0.005]	0.001 [0.019]	0.010 [0.019]	-0.009*** [0.003]
Migrant × Violence	-0.023 [0.109]	-0.000 [0.110]	-0.023*** [0.006]	0.077* [0.040]	0.021 [0.059]	0.056 [0.045]
Migrant × Climate × Violence	-0.304** [0.137]	-0.287** [0.128]	-0.017 [0.011]	0.127** [0.062]	0.137* [0.078]	-0.010 [0.018]
Climate	-0.014*** [0.005]	-0.019*** [0.005]	0.004*** [0.001]	-0.034*** [0.004]	-0.041*** [0.004]	0.007*** [0.002]
Violence	-0.078*** [0.014]	-0.081*** [0.013]	0.003 [0.004]	-0.014 [0.012]	-0.020 [0.012]	0.005 [0.006]
Climate × Violence	-0.045*** [0.015]	-0.051*** [0.015]	0.006 [0.005]	0.005 [0.013]	0.005 [0.013]	-0.000 [0.006]
Migrant	-0.089*** [0.012]	-0.080*** [0.012]	-0.009*** [0.003]	0.080*** [0.007]	0.102*** [0.007]	-0.022*** [0.002]
Observations	65,684	65,684	65,684	54,588	54,588	54,588
R-squared	0.097	0.094	0.030	0.178	0.198	0.029
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Dependent variable mean	0.504	0.484	0.020	0.795	0.769	0.026

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. This table differentiates between violence and climate shocks. Climate is a dummy variable indicator equal to 1 if the household reported being negatively affected by climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Violence is a dummy variable indicator equal to 1 if the household reported being negatively affected by armed conflict/violence/insecurity in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table A.6: Investigating heterogeneity by wealth.
The effect of shocks on labor force participation, employment, and unemployment

Panel A: Above median wealth score						
	(1)	(2)	(3)	(4)	(5)	(6)
	Female			Male		
	Labor Force Participation	Female Emp.	Female Unemp.	Labor Force Participation	Male Emp.	Male Unemp.
Migrant × Shock	0.094*** [0.036]	0.109*** [0.036]	-0.015** [0.006]	-0.009 [0.023]	-0.005 [0.023]	-0.004 [0.006]
Migrant	-0.093*** [0.013]	-0.087*** [0.013]	-0.006 [0.004]	0.076*** [0.008]	0.098*** [0.008]	-0.022*** [0.003]
Shock	-0.021*** [0.005]	-0.024*** [0.005]	0.003** [0.001]	-0.030*** [0.005]	-0.038*** [0.005]	0.008*** [0.002]
Observations	49,955	49,955	49,955	40,606	40,606	40,606
R-squared	0.085	0.083	0.030	0.157	0.177	0.030
Dependent variable mean	0.538	0.516	0.022	0.802	0.774	0.028
Panel B: Below median wealth score						
Migrant × Shock	-0.032 [0.056]	-0.026 [0.056]	-0.006* [0.003]	0.028 [0.027]	0.033 [0.027]	-0.005 [0.004]
Migrant	-0.082*** [0.026]	-0.058** [0.026]	-0.024*** [0.005]	0.107*** [0.016]	0.128*** [0.016]	-0.021*** [0.005]
Shock	0.007 [0.008]	0.001 [0.008]	0.006*** [0.002]	-0.031*** [0.007]	-0.036*** [0.007]	0.005* [0.003]
Observations	15,728	15,728	15,728	13,981	13,981	13,981
R-squared	0.097	0.098	0.027	0.246	0.272	0.027
Dependent variable mean	0.396	0.384	0.012	0.776	0.755	0.021
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age individuals. Panel A reports the results for individuals with above median wealth score, while Panel B reports the results for individuals with below median wealth score. The wealth score is computed using a Principal Component Analysis (PCA). The wealth score is computed relying on the following variables: presence of air conditioner, presence of water heater, presence of fan, a dummy for external dwelling walls being made of cement/concrete/cut stones or fired bricks, a dummy for ceiling being made of concrete slab, tile or ceiling sheets, a dummy for floor covering being made of tiles/marble or cement/concrete, a dummy variable for water access, and a dummy variable for electricity access. The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table A.7: Correlates of shocks, Logistic regression from Propensity Score Matching

	(1) Probability of witnessing shocks for women	(2) Probability of witnessing shocks for men
Age	-0.000** [0.000]	-0.000** [0.000]
Married	0.024*** [0.004]	0.009* [0.005]
No education (<i>ref: Post-secondary and above</i>)	0.229*** [0.024]	0.219*** [0.014]
Primary or less	0.190*** [0.025]	0.185*** [0.015]
Secondary	0.154*** [0.025]	0.137*** [0.015]
Upper secondary	0.059** [0.028]	0.074*** [0.017]
Rural	0.163*** [0.004]	0.158*** [0.004]
Christian (<i>ref: Muslim</i>)	-0.032*** [0.005]	-0.030*** [0.006]
Animist	0.020*** [0.007]	0.024*** [0.008]
Other religion	-0.077* [0.041]	0.026 [0.041]
No religion	0.005 [0.012]	-0.013 [0.013]
Benin (<i>ref: Togo</i>)	0.102*** [0.008]	0.092*** [0.009]
Burkina Faso	0.200*** [0.007]	0.172*** [0.008]
Guinea-Bissau	0.017** [0.008]	0.014 [0.009]
Mali	0.226*** [0.008]	0.215*** [0.009]
Niger	0.121*** [0.009]	0.117*** [0.010]
Senegal	-0.019** [0.008]	-0.028*** [0.009]
Observations	65,684	54,588

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: The table reports odd ratios following a logistic regression to predict the propensity score of witnessing shocks at the individual level. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in column (1) and to working age men in column (2).

Table A.8: Covariate balance before and after the matching on shock propensity,
Sample of women

	(1)	(2)	(3)	(4)	(5)	(6)
	Before matching			After matching		
	Treated mean	Untreated mean	Difference	Treated mean	Untreated mean	Difference
<i>Individual characteristics</i>						
Age	34.609	34.921	-0.312***	34.612	34.262	0.350***
Married	0.795	0.726	0.069***	0.795	0.793	0.001
Rural	0.761	0.526	0.235***	0.761	0.761	0.000
<i>Education</i>						
No education	0.801	0.650	0.151***	0.801	0.800	0.001
Primary or less	0.128	0.188	-0.060***	0.128	0.129	-0.001
Secondary	0.056	0.109	-0.052***	0.056	0.058	-0.002
Upper secondary	0.011	0.035	-0.024***	0.011	0.010	0.001
Post-secondary and above	0.003	0.018	-0.015***	0.003	0.003	0.000
<i>Religion</i>						
Muslim	0.726	0.670	0.057***	0.727	0.720	0.006
Christian	0.174	0.240	-0.066***	0.174	0.185	-0.011***
Animist	0.078	0.063	0.014***	0.078	0.076	0.002
Other religion	0.001	0.002	-0.001***	0.001	0.001	0.001
No religion	0.021	0.025	-0.004***	0.021	0.019	0.002
<i>Country</i>						
Benin	0.125	0.145	-0.019***	0.125	0.130	-0.005
Burkina Faso	0.263	0.152	0.111***	0.263	0.261	0.002
Guinea-Bissau	0.096	0.144	-0.048***	0.096	0.096	0.000
Mali	0.245	0.125	0.120***	0.245	0.219	0.026***
Niger	0.093	0.073	0.019***	0.093	0.115	-0.022***
Senegal	0.120	0.258	-0.138***	0.120	0.122	-0.002
Togo	0.058	0.103	-0.046***	0.058	0.057	0.001
Observations	18,146	47,538		18,142	18,142	

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The analysis is restricted to working age women (15 to 64 years old). Descriptive statistics are reported by exposure to shocks before and after PSM using nearest neighbor estimation technique. Households are exposed to shocks if they reported being negatively affected by a given shock in the three years preceding the survey. We consider shocks related to violence: armed conflict/violence/insecurity, and climate shocks such as droughts/irregular rain, floods, fires, and landslides. Columns (3) and (6) report the difference in means between women exposed to shocks and those that are not, before and after matching, as well as a t-test of whether the difference in means between the two groups is significant.

Table A.9: Covariate balance before and after the matching on shock propensity,
Sample of men

	(1)	(2)	(3)	(4)	(5)	(6)
	Before matching			After matching		
	Treated mean	Untreated mean	Difference	Treated mean	Untreated mean	Difference
<i>Individual characteristics</i>						
Age	35.757	35.875	-0.117	35.759	35.523	0.236
Married	0.667	0.633	0.035***	0.667	0.671	-0.003
Rural	0.755	0.513	0.242***	0.755	0.755	0.000
<i>Education</i>						
No education	0.676	0.493	0.183***	0.676	0.675	0.002
Primary or less	0.195	0.230	-0.035***	0.195	0.201	-0.006
Secondary	0.091	0.160	-0.069***	0.091	0.089	0.002
Upper secondary	0.026	0.065	-0.039***	0.026	0.024	0.002
Post-secondary and above	0.012	0.053	-0.040***	0.012	0.011	0.001
<i>Religion</i>						
Muslim	0.741	0.678	0.064***	0.741	0.732	0.009*
Christian	0.159	0.229	-0.070***	0.159	0.172	-0.014***
Animist	0.077	0.063	0.013***	0.077	0.074	0.003
Other religion	0.002	0.002	0.000	0.002	0.001	0.001
No religion	0.021	0.028	-0.007***	0.021	0.020	0.001
<i>Country</i>						
Benin	0.123	0.145	-0.022***	0.123	0.122	0.001
Burkina Faso	0.257	0.163	0.093***	0.257	0.269	-0.013**
Guinea-Bissau	0.092	0.140	-0.047***	0.092	0.093	-0.001
Mali	0.256	0.132	0.124***	0.256	0.229	0.027***
Niger	0.104	0.081	0.023***	0.104	0.118	-0.014***
Senegal	0.113	0.240	-0.127***	0.113	0.115	-0.001
Togo	0.054	0.099	-0.044***	0.054	0.054	0.000
Observations	15,165	39,423		15,164	15,164	

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

Notes: The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The analysis is restricted to working age men (15 to 64 years old). Descriptive statistics are reported by exposure to shocks before and after PSM using nearest neighbor estimation technique. Households are exposed to shocks if they reported being negatively affected by a given shock in the three years preceding the survey. We consider shocks related to violence: armed conflict/violence/insecurity, and climate shocks such as droughts/irregular rain, floods, fires, and landslides. Columns (3) and (6) report the difference in means between men exposed to shocks and those that are not, before and after matching, as well as a t-test of whether the difference in means between the two groups is significant.

Table A.10: Robustness checks using a double PSM technique.
The effect of shocks on labor force participation, employment, and unemployment

	Panel A: Sample of women			Panel B: Sample of men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force Participation	Emp.	Unemp.	Labor Force Participation	Emp.	Unemp.
Migrant \times Shock	0.203*** [0.058]	0.208*** [0.058]	-0.005 [0.010]	-0.003 [0.034]	0.008 [0.035]	-0.010 [0.012]
Migrant	-0.219*** [0.021]	-0.216*** [0.021]	-0.004 [0.004]	0.049*** [0.014]	0.061*** [0.015]	-0.011** [0.004]
Shock	-0.104*** [0.031]	-0.107*** [0.031]	0.003 [0.008]	-0.002 [0.020]	-0.017 [0.020]	0.015** [0.007]
Observations	4,192	4,192	4,192	4,672	4,672	4,672
R-squared	0.523	0.516	0.500	0.607	0.619	0.514
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Individual pair FE	YES	YES	YES	YES	YES	YES
Dep. var. mean	0.473	0.459	0.014	0.832	0.816	0.016

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on Propensity Score Matching followed by a standard OLS fixed effects model. Using a nearest neighbor matching technique, individuals are matched based on their propensity to witness shocks. Another PSM technique is employed on the matched sample to match migrants and non-migrants. To predict the propensity scores, the PSM technique relies on the same set of regressors included in the benchmark model at the individual level. Following the double PSM estimation, results are reported using a standard OLS fixed effects model that includes a fixed effect for each pair of matched migrant and non-migrant. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table A.11: Robustness checks using a double PSM technique. The effect of shocks on intra-household differences in labor market outcomes

	(1)	(2)	(3)
	Labor Force Participation	Employment	Unemployment
Migrant \times Shock	0.166* [0.086]	0.159* [0.086]	0.007 [0.020]
Migrant	-0.268*** [0.037]	-0.258*** [0.037]	-0.010 [0.008]
Shock	-0.081 [0.050]	-0.075 [0.050]	-0.006 [0.011]
Observations	1,602	1,602	1,602
R-squared	0.553	0.551	0.505
Household controls	YES	YES	YES
Country FE	YES	YES	YES
HH pair FE	YES	YES	YES
Dependent variable mean	-0.541	-0.551	0.010

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on Propensity Score Matching followed by a standard OLS fixed effects model. The unit of analysis is the household. Using a nearest neighbor matching technique, households are matched based on their propensity to witness shocks. Another PSM technique is employed on the matched sample to match migrant and non-migrant households. To predict the propensity scores, the PSM technique relies on the same set of regressors included in the benchmark model at the household level. Following the double PSM estimation, results are reported using a standard OLS fixed effects model that includes a fixed effect for each pair of matched migrant and non-migrant household. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The dependent variables are defined as the difference in dummy variable indicators for labor force participation, employment, and unemployment between the woman and her spouse in a given household. For labor force participation, the dependent variables takes the value -1 if the woman is not participating in the labor market, while the man is participating; it takes the value 0 if both are participating or both are not participating; and it takes the value 1 if the woman is participating, while the man is not. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include the following household controls: age of the woman and her spouse, a dummy for rural residence, the difference in the highest level of educational attainment between the woman and her spouse (no education, primary or less, secondary, upper secondary, post-secondary and above), and dummies for the religion of the household head (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects for the household head: Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table A.12: Robustness checks including Ivory Coast.
The effect of shocks on labor force participation, employment, and unemployment

	Panel A: Sample of women			Panel B: Sample of men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force Participation	Emp.	Unemp.	Labor Force Participation	Emp.	Unemp.
Migrant \times Shock	0.061** [0.031]	0.073** [0.031]	-0.012*** [0.004]	0.003 [0.018]	0.005 [0.018]	-0.002 [0.005]
Migrant	-0.092*** [0.012]	-0.080*** [0.012]	-0.012*** [0.003]	0.080*** [0.007]	0.104*** [0.007]	-0.024*** [0.002]
Shock	-0.017*** [0.004]	-0.021*** [0.004]	0.004*** [0.001]	-0.027*** [0.004]	-0.033*** [0.004]	0.006*** [0.001]
Observations	77,147	77,147	77,147	64,516	64,516	64,516
R-squared	0.089	0.084	0.033	0.178	0.199	0.029
Individual controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Dependent variable mean	0.506	0.486	0.021	0.803	0.777	0.026

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The analysis additionally includes information on national citizens of Ivory Coast. The sample is restricted to working age women in columns (1) to (3), and to working age men in columns (4) to (6). The dependent variables are dummy variable indicators for labor force participation, employment, and unemployment. Migrant is a dummy variable indicator equal to 1 for WAEMU immigrants in Ivory Coast and equal to 0 for non-migrants in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include individual controls such as: age, marital status, a dummy for rural residence, highest level of educational attainment (no education, primary or less, secondary, upper secondary, post-secondary and above), and religion dummies (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects: Benin, Burkina Faso, Guinea Bissau, Ivory Coast, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.

Table A.13: Robustness checks including Ivory Coast.
The effect of shocks on intrahousehold differences in labor market outcomes

	(1) Labor Force Participation	(2) Employment	(3) Unemployment
Migrant × Shock	0.092** [0.043]	0.094** [0.043]	-0.002 [0.007]
Migrant	-0.188*** [0.016]	-0.179*** [0.016]	-0.009** [0.004]
Shock	-0.018** [0.008]	-0.014* [0.008]	-0.004* [0.002]
Observations	26,762	26,762	26,762
R-squared	0.094	0.090	0.007
Household controls	YES	YES	YES
Country FE	YES	YES	YES
Dependent variable mean	-0.417	-0.428	0.010

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in brackets.

Notes: Each cell presents a coefficient estimate relying on an OLS fixed effects model. The analysis relies on data from the EHCVM surveys conducted in two waves in 2018 and 2019. We rely on data on the WAEMU immigrant population in Ivory Coast, as well as data on non-migrants from the surveys conducted in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal, and Togo. The analysis additionally includes information on national citizens of Ivory Coast. The unit of analysis is the household and the analysis is restricted to married couples of working age. The dependent variables are defined as the difference in dummy variable indicators for labor force participation, employment, and unemployment between the woman and her spouse in a given household. For labor force participation, the dependent variable takes the value -1 if the woman is not participating in the labor market, while the man is participating; it takes the value 0 if both are participating or both are not participating; and it takes the value 1 if the woman is participating, while the man is not. Migrant is a dummy variable indicator equal to 1 for WAEMU migrant households in Ivory Coast and equal to 0 for non-migrants households in the WAEMU countries. Shock is a dummy variable indicator equal to 1 if the household reported being negatively affected by violence: armed conflict/violence/insecurity, or climate shocks such as droughts/irregular rain, floods, fires, and landslides, in the three years preceding the survey. Regressions include the following household controls: age of the woman and her spouse, a dummy for rural residence, the difference in the highest level of educational attainment between the woman and her spouse (no education, primary or less, secondary, upper secondary, post-secondary and above), and dummies for the religion of the household head (Muslim, Christian, Animist, no religion or other religion). Regressions also include country of origin fixed effects for the household head: Benin, Burkina Faso, Guinea Bissau, Ivory Coast, Mali, Niger, Senegal, and Togo. Dependent variable means are reported in the last row.