School or work?
The role of weather shocks in Madagascar[1]

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Abstract

Climate change is particularly important issue in Madagascar, a poor island nation that is frequently affected by droughts, floods and cyclones. We examine the impact of weather events on schooling and work among a cohort of teens and young adults by estimating a bivariate probit model using data from 210 localities over the period 2004 to 2011. Our results show that rainfall deviations and cyclones reduce the probability of attending school and push young men, and to a great extent women, into the work force. Hardest hit are the less wealthy households, as one would expect, given their more limited savings, and access to credit and insurance which limits their ability to cope with negative weather shocks. We observe both contemporaneous and lagged effects of the weather shocks which are of a similar magnitude.

1. Introduction

Weather events can affect human capital formation and have long-lasting impacts on individual well-being and the overall macroeconomy. These events are of particular concern in developing countries that are poor, lack credit and insurance markets, and are heavily reliant on the agricultural sector, which is particularly vulnerable to climate shocks, for employment and income. In this paper, we focus on the impact of weather on schooling and work decisions in Madagascar. The concern over vulnerability to climate variability is of heightened concern in

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Madagascar, since it is one of the ten countries in the world with the highest Climate Risk Index (Kreft et al., 2016); hurricanes, floods, and drought heavily affect the country's fragile ecology and agricultural economy where 74.5 percent of the population is employed[2]. According to USAID,[3] climate scientists expect flooding and erosion to increase in some regions of the country, as rainfall increases in intensity, while in the south, rainfall will be less predictable, leading to greater extremes, including intermittent drought. Therefore, in this paper, we study the impact of weather events and shocks on schooling and entry into the labor market in Madagascar, using panel data on a cohort of young men and women who were between 21 and 23 years old in 2011, and were initially surveyed in 2004, when they were in their young teenage years, together with commune census and satellite-based rainfall data. More specifically, we estimate a bivariate probit model of schooling and work for these young adults cohort members (CMs) who reside in rural areas of Madagascar, with time and geographical fixed-effects. The identification strategy relies on the large temporal and spatial historical variations in rainfall between 2004 and 2011, across 210 localities. Results show that positive rainfall deviations from the long term average increase the probability of school enrollment, while reducing the probability of being engaged in work. We also find that cyclones reduce the probability of being enrolled in school.

This paper is part of a rapidly growing body of research, which examines how extreme weather events influence economic outcomes (Dell et al., 2014), and more specifically, human capital. Weather events are found to have a significant impact on human capital through several dimensions: income (Levine and Yang, 2014); wages (Mahajan, 2017); nutrition and health (Maccini and Yang, 2009; Tiwari, Jacoby, and Skoufias, 2017); and consumption and calorie intake (Asfaw and Maggio, 2017). More relevant to our specific interest in schooling and work, Villalobos (2016) found that daily meteorological variations (precipitation and heat) had a deleterious impact on schooling outcomes in Costa Rica, and that students in more humid and warmer villages were at a higher risk of absenteeism and poor academic outcomes. Groppo and Kraehnert (2017) showed that students living in Mongolian districts affected by severe winters were less likely to complete mandatory school. The impacts were significant only for students living in herding households. The authors concluded that the effects were not associated with increased child labor in herding or with schools closure, but rather the effects were related to the

[2] World Development Indicators (the data refer to 2015).
[3] https://www.usaid.gov/madagascar/environment

drop in household income due to the loss of livestock. Maccini and Yang (2009) found that favorable rainfall conditions, occurring in the year of birth, have a positive effect on educational outcomes for adult Indonesian women. Jensen (2000) estimated that adverse rainfall conditions in Côte d'Ivoire decrease school enrollment of children.

Regarding the effects on labor outcomes, Jacoby and Skoufias (1997) found that households respond to negative income fluctuations, generated by weather shocks, by withdrawing their children from school in order to increase labor market engagement, with possibly long-lasting negative effects on poverty and development. Shah and Steinberg (2017) found that positive rainfall conditions increased average wages in the Indian rural sector. This encouraged parents to increase their children's on-farm labor supply and, as a consequence, schooling participation decreased. Rainfall shocks, in this context, act as a "productivity wage shifter". In other words, households could be motivated to lower human capital investments in their children's education, when wages for low-paying unskilled jobs increase. Also, authors found that higher rainfall in early life (in utero to age 2 years) had a positive impact on math and reading tests, and reduced the probability of being behind in school or of having never been enrolled. Finally, Dumas (2015) showed that child labor increased with higher rainfall in Tanzania in the absence of efficient labor markets. This effect is explained by what she calls the "price effect": the increase in labor productivity pushed parents to make their children work on the family farm.[4]

Overall, the existing literature suggests that a positive weather event and, more specifically, a positive deviation in rainfall, can have ambiguous effects on schooling and labor, but this strongly depends on the context. This ambiguity reflects the conflicting income and price effects associated with shocks. That is, we might observe an income effect whereby a positive shock increases agricultural production, so that parents are able to send children to school for longer periods, with their entry into the labor market postponed. Conversely, we could also observe a price effect: the increase in labor productivity associated with better climatic conditions encourages parents to have their children work, thus increasing the probability of school dropout. Besides these conflicting income and price effects, we also examine the expected

[4] The literature also explores the impact of weather events on the diversification choice. For example, Skoufias, Bandyopadhyay, and Olivieri (2017) showed that *ex ante* rainfall variability in India was associated with more diversification of rural households from agricultural to off-farm sectors. Similarly, Bandyopadhyay and Skoufias (2015) found that *ex ante* rainfall variability risks in Bangladesh pushed adult members that were not the heads of their households away from the agricultural sectors, also at a cost of a lower total household welfare.

negative impact of climatic events that destroy infrastructure, particularly cyclones, on schooling. These acute weather shocks can destroy roads, interrupt electricity and damage schools, contributing to school dropout. Thus, we add to the limited evidence on the impact of rainfall deviations in a country with high climatic variability as well as widespread poverty and absent or incomplete credit and insurance markets; in combination these characteristics exacerbate the impact of shocks and limit the scope for mechanism to cope with such climate variability. In addition to seeing how shocks impact schooling and work, we also address the extent to which household and community conditions affect the response to climatic events.

In the remainder of the paper, we next present a conceptual framework, followed by a description of the context and the data we employ in Section 3. Section 4 presents the estimation strategy, and we report the results in Section 5. Finally, in Section 6, we conclude and discuss the implications of our results for policy.

2. Conceptual framework

Weather shocks can have immediate and lagged effects on school and work decisions. In this study, we define negative weather shocks, which can contribute to drought conditions, as rainfall events that are below the historical local trend. Conversely, a positive weather shock occurs when the rainfall deviation from the historical local trend is above zero. In considering these positive and negative deviations, the underlying assumption is that with less rain, the worse it is in terms of productivity and yields; while with more rain, the better - except in the instance when these positive deviations are large and are associated to floods. Such acute rainfall events occur primarily as cyclones, which are distinguished, and differentiated from normal weather deviations in our models. Positive and negative shocks, in turn, can have contemporaneous and/or lagged effects on decisions to drop out of school and enter the labor market, and thus, have an impact on human capital formation of those whose choices are affected.

Figure *1* shows the definition of our school, work, and rainfall variables, with respect to the months of the year. For the purpose of our analysis, we considered individuals in school in year *t*, if they were attending and completed school in the schooling year that began in September of the year *t-1* (i.e., they did not drop out from school before June of year *t*). We considered individuals at work in year *t*, if they reported having been employed, including unpaid work in a family enterprise, on or before May in year *t*. Thus, we did not consider them working in year *t*, if they started working after June in year *t* (for these individuals, we assigned a working status for the year *t+1*). Our rainfall variable in year *t* is defined over the period November (*t-1*) through April (*t*), which broadly corresponds to the rainy season throughout the country. Since our research focuses on rural areas, we defined our outcomes in accordance with the agricultural season of rice, which is the main crop in Madagascar. More than two-thirds of our sampled individuals reported rice as the main cultivated crop. And, while maize is an important secondary crop, its agricultural calendar closely resembles that of rice.[5]

The availability of the exact month in our survey data allows us to determine when the CM left school and/or started to work. This is important to distinguish between immediate (or contemporaneous) and lagged effects of rainfall deviations on schooling and working decisions. As for the contemporaneous effect, CMs may or may not complete their school year depending on the current year's rainfall, a decision that is expected to affect the households' revenues in the current agricultural season. In our models, these immediate effects may result in the CM leaving school before the beginning of the harvest season in June.

Concerning the lagged effects, households may decide to keep their children at school (e.g., to pursue a new schooling year in September) or send them to work (e.g., by around November, at the start of the next agricultural season), depending on the production of, and revenues generated from, the crops grown in the previous rainy season. The decision as to whether a child remains in school during the agricultural cycle that follows the agricultural season in which the shocks take place represents the lagged effects, which are captured by the rainfall variable observed in *t-1* on school or work status in *t*.

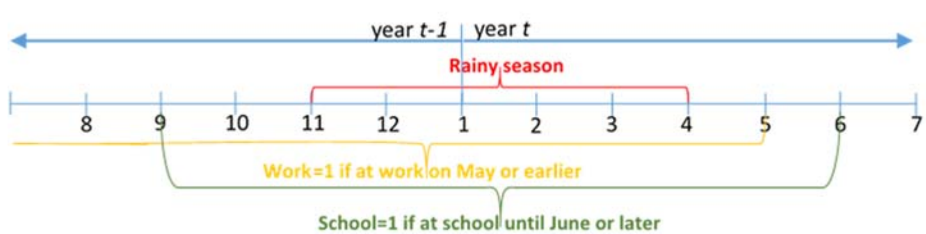

Figure 1: Definition of school, work, and rainfall variables

Source: Authors' elaboration
Notes: On the horizontal axis, we report the months of the year.

[5] See http://www.fao.org/agriculture/seed/cropcalendar/welcome.do

While our non-separable household model allows us to explore how climate shocks affect schooling and work decisions, we cannot distinguish whether these decisions are primarily mediated by income effects or changes in the shadow price of labor. That is, we posit that there are three possible mechanisms whereby climate shocks contribute to leaving school and entering the labor market:

1. Income (direct) effects, which given that schooling is a normal good, are expected to increase the likelihood of staying in school and reduce the likelihood of entering the labor market, especially since there will be less need to pull their children out of school to help cope with the decline in agricultural output and earnings.
2. The pure price (indirect) effect of changes in the returns to, or shadow price of labor. In the case of positive rainfall shocks, these shadow wages are expected to increase, and just the opposite in the case of negative shocks. The expected impact of changes in the shadow price of labor on schooling and labor market entry of the cohort members is ambiguous and depends on a range of factors, including the relative changes in the shadow price and wage of other household members, and changes in prices of other complementary inputs and substitutes. Making matters particularly complicated in terms of signing the pure price effect are the expected imperfections in the labor and credit markets and the potential availability of surplus labor. All in all, the price effect is zero if markets are complete. With market imperfections, the expected increased productivity can be absorbed by raising the CM's working time on the farm (which would likely negatively impact on schooling) or by increasing on-farm work of CM's family members if underemployed (in such a case, there would be no effect on CMs' schooling), or both the effects.
3. Infrastructure effects, from cyclones destroying schools, roads, electric grids, and other physical structures that would prevent children from attending school.

However, we are not able to disentangle the relative importance of these in impacting schooling and work decisions. Instead, our analysis is limited to testing for the existence of contemporaneous and lagged effects. For example, in the case of the negative income effect from a lower rainfall leading to drought, we examine whether this effect is felt immediately, as evidenced by the CMs dropping out of school during the agricultural season in which the rainfall shock occurs, or instead, choosing not to enroll in school and instead to work in the academic year subsequent to the shock. In the case of positive deviations in rainfall, we also examine contemporaneous and lagged effects: better rains lead to higher family income, which may both increase the likelihood that a CM remains in school during the current agricultural calendar, but also may encourage parents to enroll the CMs in school the following academic year, instead of having them enter the labor market. In the case of cyclones, we only look at contemporaneous impacts of the destruction of infrastructure.

Finally, we test for the existence of heterogeneity to vulnerability. Pre-shock assets can help households mitigating shocks as they can be used as buffer stocks and as collateral for credit loans, especially in the case of transitory shocks. But, such a capacity can differ by households' assets holding. We then expect that weather shocks impact differently on CMs depending on their households' ability of buffering shocks, which in this paper is proxied by a household wealth index at the initial period.

3. Context, data, and descriptive statistics

Madagascar's geography, located between the Indian Ocean and the Mozambique Channel, often makes the island the terminus of tropical cyclones and storms that originate on the western coasts of Australia. Most of the regions of the country are classified as high risk for cyclones, with the Eastern Coast being the most affected. The frequency of tropical cyclones is expected to decline in the next decades, but their intensity will increase (Mavume et al., 2009; Hervieu, 2015). The country is particularly vulnerable to tropical cyclones due to the lack of good disaster warning strategies (Fitchett and Grab, 2014). Between 2000 and 2012, a number of tropical cyclones have hit Madagascar, with cyclones Elita and Gafilo, the most devastating storms that occurred over that period, specifically in 2004, having killed more than 200 people and destroyed about 1,400 schools all over the country (Rajaon et al., 2015).

Besides strong winds, tropical storms are accompanied by heavy rains and flooding. Floods are, thus, very common in the country, and their frequency is increasing. While the East coast is most affected from tropical storms, the southwest and the extreme south suffer from chronic lack of rain. The past three years have been characterized by a prolonged drought, which has been exacerbated by an exceptionally strong El Niño in the 2015–16 season. According to the Food and Agriculture Organization of the United Nations (FAO), El Niño has resulted in the lowest precipitation in 35 years.[6] Drought has, in turn, contributed to crop failures, disease, and malnutrition. According to the United Nations Children's Fund (UNICEF), at the beginning of the academic year 2015–16, parents started to take children out of school, when teachers' and students' absenteeism increased as a result of drought conditions (UNICEF, 2016). And while rainfall is expected to intensify in some regions of Madagascar, especially those vulnerable to cyclones, lower rainfall is projected in the south of the country.[7] It is not only its extreme vulnerability to weather events that makes Madagascar an interesting case to study for impact on schooling and work, but additionally, the fact that about one-fourth of GDP in Madagascar is from the agricultural sector, which employs about 75 percent of the population. And, the vast majority of agricultural landholdings are small-scale, rainfed farms, where output and incomes are highly sensitive to rainfall patterns and extreme weather events.

In this paper, we use individual data from two surveys: the *Madagascar Life Course Transition of Young Adults Survey* (2011–2012) and the *Progression Through School and Academic Performance in Madagascar Study* (EPSPAM, 2004). These are the two latest rounds of a survey that follows a cohort of young adults (now), born in the late 1980s. The sample in the cohort was based on a survey, *Programme d'Analyse des Systèmes Educatifs de la CONFEMEN* (PASEC), conducted with second-grade students in 1998, who were from randomly selected schools throughout the country. This school-based sample, however, was not representative of young children in that age range because many children were not enrolled in school, and schools that were very small and had few students per grade were excluded. To partially address this issue, the 2004 survey supplemented the 48 PASEC clusters with an additional 12 clusters, randomly selected from rural communities, with small primary schools defined as having classrooms with less than 20 students. These additional schools were randomly selected from the list of schools in the Ministry of Education database. In these new clusters, we also did a complete enumeration of all the children in the cohort's age range, and randomly selected 15 children of the same age as those of the original PASEC sample. In addition, in each of the original PASEC clusters, we did a complete enumeration and selected 15 children who were *not* in the original PASEC sample. This was to make sure that we did not exclude those who never attended school, or enrolled very late, which is not an uncommon occurrence in Madagascar. Thus, the 2004–5 and 2011–12 samples

[6] See http://www.fao.org/news/story/en/item/382932/icode/ (accessed on July 2017).
[7] See https://www.usaid.gov/madagascar/environment (accessed on July 2017).

include cohort members who would not have been selected by the original school-based survey, because they dropped out of school early or never attended. This sampling approach was designed to make the cohort nationally representative, or at least get close to that objective. Comparisons of descriptive statistics of the cohort with other nationally representative surveys indicate that we were able to achieve this objective (Aubery and Sahn, 2017; Herrera and Sahn, 2015).[8]

Both the 2004 and 2012 surveys collected comprehensive information on cohort members and their family members. The questionnaire included modules on education, labor, migration, entrepreneurship, agriculture, family enterprises, health and fertility, and cognitive abilities, as well as household assets and housing conditions. The cohort based sample also collected considerable retrospective data using recall techniques, so, for example, we know the exact month and year that a cohort member left school, the precise timing of entry into the labor force, and the type of work performed. The cohort-based sample was complemented by community surveys of social and economic infrastructure, as well as general information on the key historical developments in the villages. We have information on 1,119 cohort members living in rural areas, aged 21 to 23 at the time of the 2012 survey. Among them, 316 rural cohort members (CMs) left their community of origin between 2004 and 2012 to move to another Malagasy locality: we defined them as (internal) migrants.

Figure 2 shows the school-to-work transitions, by age of our cohort members, during the period 2004 to 2011. As expected, older members are less likely to attend school, while the share of those CMs engaged in economic activities increases rapidly with age. Also, individuals both attending school and working decrease over time, and the circumstance of being neither at school nor at work occurred most likely when cohort members were 18 and 19 years old. In our sample of rural CMs, no one who dropped out of school returned at a later date. A negative shock that will induce people to leave school, such as rainfall deficit events, will therefore affect individual decisions permanently, and at least in the case of schooling, lower human capital accumulation among teens and young adults.

[8] The reality is that no survey in Madagascar conducted in the past decade can really be considered nationally representative, since the most recent census, upon which sampling frames have been built, was conducted in 1993.

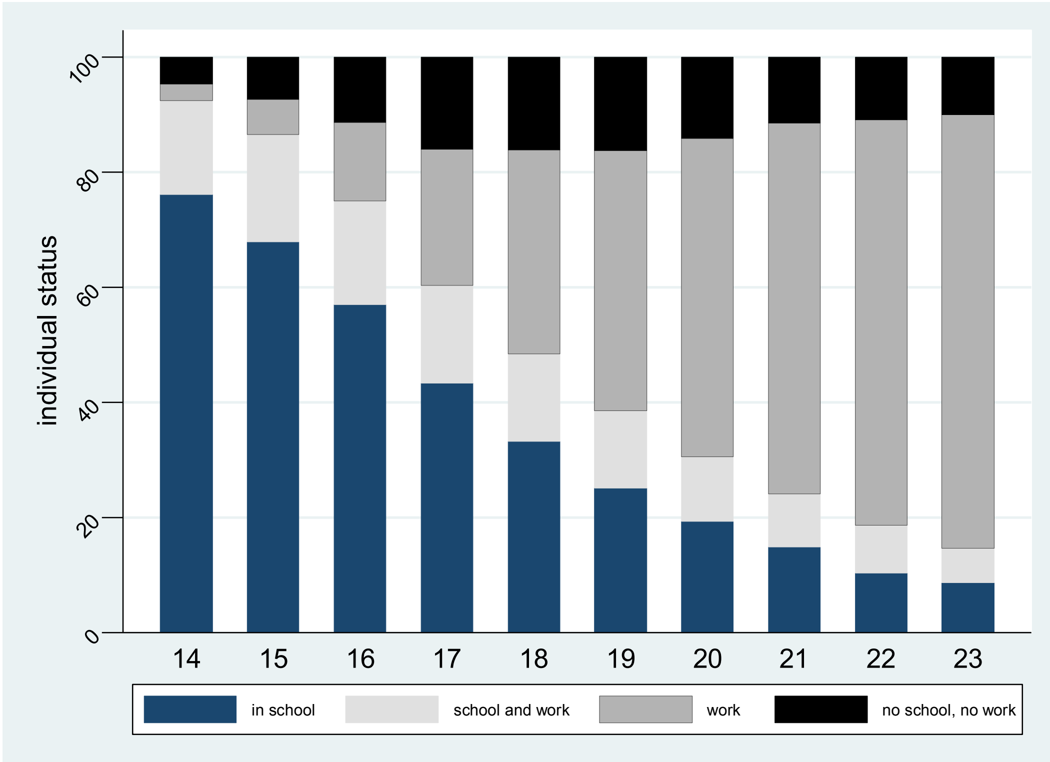

Figure 2: School-to-work transition between 14 and 23 years old (in 2004–2011), rural cohort members

Source: Authors' estimation based on *Madagascar Young Adult Survey*

Cohort members were, on average, 14.87 years old in 2004, and about half of them are women (Table 1). About 70 percent entered school between 5 and 7 years old, but the sample also contains 6 percent of individuals who entered school after age 10. The vast majority of parents are working, although this share is lower in 2012 than 2004, as would be expected as parents' age increases. While our paper focuses on climate shocks, we are also interested in the role of, and interaction with, other household shocks, particularly health shocks, in affecting employment. We find that the percentage of parents who suffered from any illness or disability increases between the 2004 and 2012 surveys,[9] as does the percentage of parents who died. About 50 percent of fathers have no education, while the comparable figure for mothers is 60 percent. Primary school is the highest level of completed education for 18 percent of fathers and 23 percent of mothers, while lower middle school has been completed by 32 per cent of fathers and half as many

[9] The questionnaire asks cohort members the following question: "Did your father (your mother) have any illness or disability, or an injury during the last seven years (since 2004), which prevented him (her) from working or carrying on business for a month or more?"

mothers. Concerning economic activity, the vast majority of fathers are own-account workers, with the remaining 35 percent of them employed as wage workers or as family workers. Mothers are primarily employed as family workers (45 percent) or own-account workers (40.5 percent); only a small percentage is employed as wage workers or housewives.[10]

About 46 percent of cohort members left their original households between 2004 and 2011 and are now living in newly formed households. Twenty-eight percent of the cohort members have migrated out of their community during this time period. The number of households cultivating land, irrespective of whether the land is owned or not, has increased over time.[11] Finally, in Table 1, we present the household asset index in 2004, a measure of wealth (based on non-land assets), computed using factor analysis on data observed in 2004, following the procedure used by Filmer and Pritchett (2001).

[10] We were not able to observe changes in parents' working activities over time. In order to build this variable, we used the answers collected in 2011. Working status refers to 2011 for those parents who are still economically active, while it refers to the time of retirement for the inactive ones, and to the time of death for those no longer alive.

[11] The household questionnaire contains a section that collects information on the history of the exploited lands.

Time-varying characteristics	Mean (2004)	Sd (2004)	Mean (2011)	sd (2004)
Age (years)	14.87	0.81	21.87	0.81
Father is dead	7.06	0.26	14.03	0.35
Father is ill	0.80	0.09	4.74	0.21
Mother is dead	4.74	0.21	8.85	0.28
Mother is ill	1.07	0.10	3.84	0.19
Father works	91.25	0.28	81.33	0.39
Mother works	90.19	0.30	86.14	0.35
CM lives in a new household	1.34	0.16	46.47	0.50
Brothers less than 18 years old (number)	0.60	1.04	0.42	0.85
Sisters less than 18 years old (number)	0.53	0.94	0.39	0.82
Migrant	3.57	0.19	28.24	0.45
Household cultivates land	40.93	0.49	72.65	0.45
Middle school in village	71.49	0.45	77.93	0.41
High school in village	20.73	0.41	45.31	0.50
Time-invariant characteristics	**Mean**		**sd**	
Female	51.12		0.50	
Age at school entry (years)	6.95		1.82	
Father has no education	50.04		0.50	
Father has completed primary	17.42		0.38	
Father has completed college	32.53		0.47	
Mother has no education	60.50		0.49	
Mother has completed primary	23.32		0.43	
Mother has completed college	16.18		0.37	
Household assets in 2003 (0 to 100)	20.23		16.65	
Land type, coastal plain	10.44		0.30	
Land type, interior plain	11.28		0.33	
Land type, hill	46.97		0.49	
Land type, plateau	16.03		0.36	
Land type, valley	12.86		0.33	
Land type, others	2.42		0.15	
Paved road in village	12.69		0.33	
Number of observations	*1,119*			

Table 1: Descriptive statistics

Source: Authors' estimations from *Madagascar Young Adult Survey* and *EPSPAM*

Notes: If not specified differently, variables are expressed in percentages.

In our models, we also rely on data from the community questionnaire, especially for a question on the topography of the village where individuals live. More specifically, we create a classification with the following categories: hills, where 47 per cent of cohort members live, coastal plains (10.5%), interior plains (11.3%), plateau (16%), valleys (13%), and others. The community questionnaire also provides information on the presence of the middle and high schools, as well as information about their year of construction, which we use in our models.

In terms of our focus on the impact of climate and weather data on schooling and work, we use the Köppen–Geiger climate classification system in order to identify the climatic zones of the country. This system first classifies geographical areas into five main climate groups: tropical, dry, temperate, continental and polar. Then it classifies each group by the seasonal precipitation type and the level of heat. According to this classification, Madagascar is divided into eight climatic zones, as shown in Table 2. This table shows the distribution of the cohort members, corresponding to the climatic zones where they lived in 2004 and in 2011.

Climatic zones	2004 (percentage)	2011 (percentage)
1. Equatorial rainforest, fully humid	15.64	16.53
2. Equatorial monsoon	19.48	17.16
3. Equatorial savannah with dry winter	13.05	14.39
4. Steppe climate (hot steppe)	4.02	4.02
5. Warm temperate, fully humid (hot summer)	7.33	7.69
6. Warm temperate, fully humid (warm summer)	20.64	18.86
7. Warm temperate, dry winter (hot summer)	11.35	10.72
8. Cwb. Warm temperate, dry winter (warm summer)	8.49	10.63

Table 2: Climatic zones

Source: Authors' estimations from *Madagascar Young Adult Survey*

Data on cyclones are taken from the *Tropical cyclones windspeed buffers 1970–2015*, that is provided by the *Global Risk Data Platform.*[12] We have information on the number and the strength of cyclones that hit sample communities. The strength of a cyclone is measured through the Saffir–Simpson hurricane wind scale (SSHWS). This scale classifies cyclones into five categories on the basis of the wind speed, from 1 (minimal strength, between 119 to 153 km/h) to 5 (maximal strength, more than 252 km/h). We also have information on tropical storms, which are approximately 63-118 km/h in wind speed.

Figure A.2 shows how the localities where our cohort members live have been affected by cyclones over the period, 2004 to 2012. Table 3 indicates that in 2004, when cyclones Elita and Gafilo hit Madagascar, almost 60 percent of cohort members were directly impacted by a tropical

[12] Data available at:
http://preview.grid.unep.ch/index.php?preview=data&events=cyclones&evcat=1&lang=eng

storm, while almost 15 percent were hit by a tropical cyclone. The percentages were much lower for the following years, especially concerning tropical cyclones.

Year	% of CM hit by at least a tropical storm or a tropical cyclone	% of CM hit by at least a tropical cyclone strength ≥ 1
2004	64.34	14.75
2005	10.99	0.09
2006	28.95	0.09
2007	27.17	2.06
2008	37.27	0.00
2009	26.18	2.23
2010	2.06	0.00
2011	4.20	0.00

Table 3: Cohort members hit by cyclone, in %

Source: Authors' estimations from *Global Risk Data Platform* and *Madagascar Young Adult Survey*

Rainfall data is derived from the African Rainfall Climatology, version 2, National Oceanic and Atmospheric Administration. They are gridded daily precipitation estimates centered over Africa at 0.1 degree (about 10 x 10 km) spatial resolution (from 1983 to 2012).[13]

In this study, we employ several rainfall-based indicators. First, we estimate the standardized rainfall deviations over the period November-April (rainy season),[14] by taking the variation between the total amount of rain precipitation over these months in year *t* in locality *l* and the 1991–2011 average, normalized by its 1991–2011 standard deviation. Unfortunately, because of many missing values for the period 1983–1990, we could not use rainfall data earlier than 1991. This indicator captures (positive or negative) rainfall deviations with respect to the local long-term average. Also, given that the measure is standardized to the locality's average, differences in the yearly deviations across rainy and dry zones are comparable.

[13] We also tried to use CRU 3.24 data, gridded data that interpolate between the ground stations with a resolution of 0.5 x 0.5 degrees, but we realized that these data presented missing values, replaced by the long-term average, for a large number of sample communities between 2006 and 2009. This was due to the lack of weather stations available within the radius that is used for rainfall and temperature observations. We thus decided not to use CRU data due to their poor quality for our case study. We also wanted to use the Standardized Precipitation Evapotranspiration Index (SPEI) to take into account the effect of evapotranspiration, but, unfortunately, the SPEI database is based on CRU data for rainfall.

[14] Although there are some differences with respect to the beginning and the end of the rainy season within the country, in most of the areas, this season goes from November to April, with a few others experiencing a slightly shorter rainy season
(see http://www.fao.org/agriculture/seed/cropcalendar/welcome.do, accessed on September, 2017).

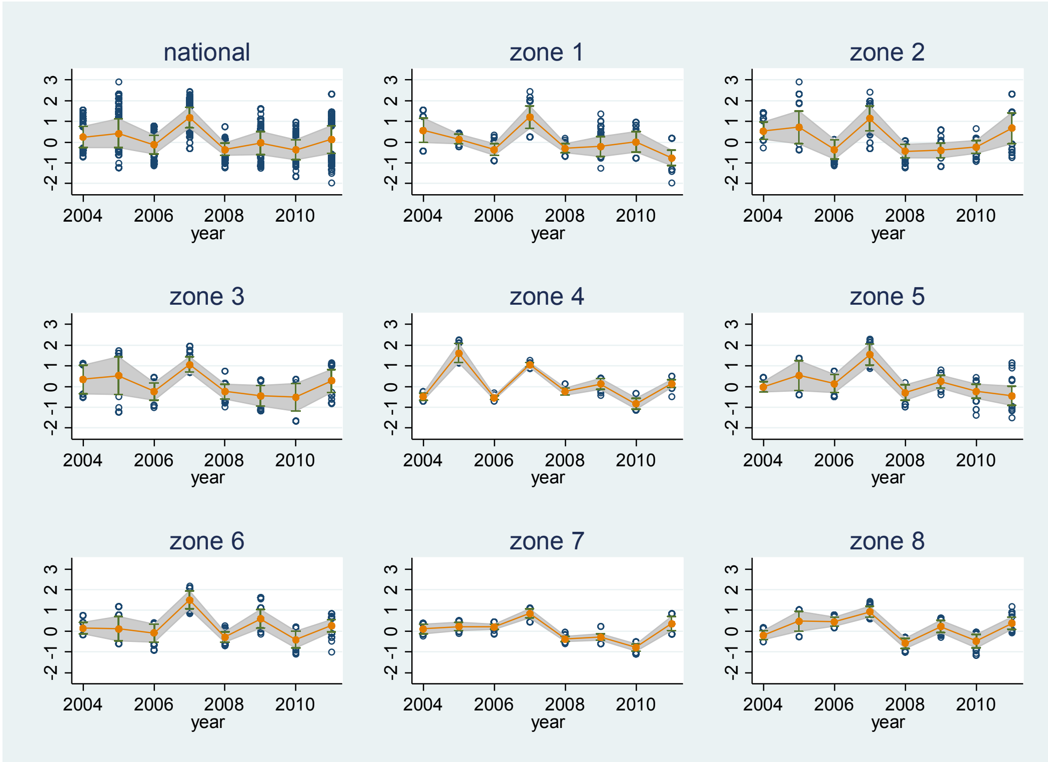

Figure 3: Rainfall deviation from the long-term, national mean, and by climatic zones (2004–2011)

Source: Authors' estimation

Notes: For the definition of climatic zones, see Table 2.

shows the trend of the standardized rainfall deviation between 2004 and 2011, both at a national level and by climatic zone. Over this period, the standardized rainfall deviation ranged between -1.96 and 2.89, relative to the long-term average. There are differences across climatic zones, which are useful for our analysis, as the positive (or negative) rainfall deviations vary across localities. Left panel of Figure 4 shows the distribution of the rainfall deviation variable over the period 2004 to 2012 for all rural localities. Right panel shows the distribution of the mean of the same variable calculated by locality over the whole period. When we compare the two figures, we observe that the distribution of the locality mean is more concentrated around zero. This confirms that, on average, rainfall deviation from the mean is zero over the period in our sample localities. In other words, the localities in our sample are not systematically characterized by a positive or by a negative rainfall deviation. In fact, when we regress rainfall deviation on its lagged value, the lagged value is not significant.

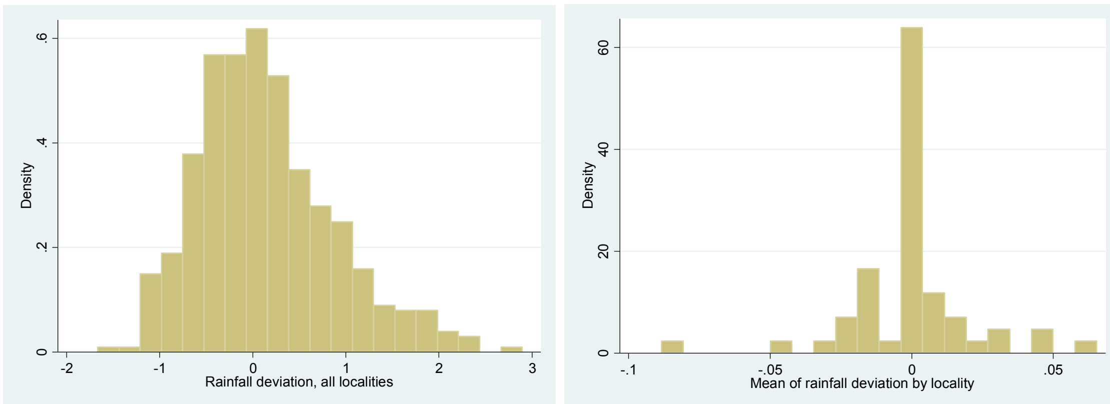

Figure 4: Distribution of rainfall deviations (left panel) and distribution of the mean of rainfall deviation by locality (right panel)

Source: Authors' estimation

Based on the standardized rainfall indicator, we identified exclusive categories to capture, in particular, extreme rainfall shocks.[15] We also defined a variable *drought*, that takes value 1 if rainfall deviation is lower than 1 at time *t.* Finally, we used a relative seasonality index to capture the degree of variability of rainfall through the period November-April for each year. Following Walsh and Lawler (1981, p. 202), we defined the seasonality index as "the sum of the absolute deviations of mean monthly rainfalls from the overall monthly mean, divided by the mean […] rainfall" over November-April. This index can range between 0 (if rainfall is distributed equally across months) and values equal to or higher than 1.20 (in such a case we would talk of extreme inequality in rainfall and almost all rain would fall in 1 or 2 months).

4. Estimation strategy

We assume that schooling and work decisions are interdependent. A cohort member can choose to be only at school, only at work, sharing her time between school and work, or being neither at school nor at work. To allow interdependency of the different alternatives, we adopted a

[15] These are defined as follows: category 1 if rainfall deviation is lower than -1; category 2 if rainfall deviation ranges between –1 and 0; category 3 if rainfall deviation ranges between 0 and 1; category 4 if rainfall deviation ranges between 1 and 2; category 5 if rainfall deviation is higher than 2.

bivariate probit model where we define S^* and W^*as the latent variables of attending school (S) and participating in work activities (W), respectively,[16] and defined (in its basic specification) as:

$$S^*_{ict} = \boldsymbol{\beta}^S_1 X_{ict} + \boldsymbol{\beta}^S_2 rain_{lt} + \boldsymbol{\beta}^S_3 rain_{lt} * asset_{i2004} + \theta^S_{it} + \mu^S_z + \theta^S_t + \boldsymbol{\varepsilon}^S_{ict}$$
$$W^*_{ict} = \boldsymbol{\beta}^W_1 X_{ict} + \boldsymbol{\beta}^W_2 rain_{lt} + \boldsymbol{\beta}^S_3 rain_{lt} * asset_{i2004} + \theta^W_{it} + \mu^W_z + \theta^W_t + \boldsymbol{\varepsilon}^W_{ict}$$

where:

$$S_{ict} = \begin{Bmatrix} 1 \; if \; S^*_{ict} > 0 \\ 0 \; if \; S^*_{ict} \leq 0 \end{Bmatrix}$$
$$W_{ict} = \begin{Bmatrix} 1 \; if \; W^*_{ict} > 0 \\ 0 \; if \; W^*_{ict} \leq 0 \end{Bmatrix}$$

In this model, S_{ict} takes the value of 1 if the cohort member *i* living in rural community *c* was enrolled in school during year *t*, and W_{ict} equals 1 if the cohort member was engaged in economic activities. The definition of the school and work variables have been detailed in Section 2 (also refer to Figure 1). X_{ict} is a set of explanatory variables that are characteristics of the cohort member, and of the community and household in which she resided in 2004, including of her parents as described in Section 3. The variable $rain_{lt}$ is one of the rainfall variables described in the previous section, as observed in the community where the CM lived in the year *t*. By introducing the interaction of the rainfall variable with a household wealth index in 2004, which is the initial year of the analysis, we allow for heterogeneous effects across households, and, more specifically, we can control for their resilience to climatic shocks, which is hypothesized to vary according to the CM's initial wealth. We control for the CM's age (denoted by dummies θ_{it}), climatic zones z (μ_z), and the year (θ_t). The inclusion of these fixed effects ensures that our results are not biased by systematic differences related to these variables. Finally, $\boldsymbol{\varepsilon}^S_{ict}$ and $\boldsymbol{\varepsilon}^W_{ict}$ are normally distributed error terms, with $cov\left(\boldsymbol{\varepsilon}^S_{ict}, \boldsymbol{\varepsilon}^W_{ict}\right) = \rho$. Standard errors are clustered at the climatic-station level. With our data, an unbiased identification of $\boldsymbol{\beta}_2 \; and \; \boldsymbol{\beta}_3$ is possible because of the large temporal and spatial variation in the locality-level rainfall deviations, which should not be correlated with any unobserved variables affecting school and work decisions ($\boldsymbol{\varepsilon}^S_{ict}$ and $\boldsymbol{\varepsilon}^W_{ict}$).

[16] As to why we did not use a probit with fixed individual effects, most of the variables used in our estimations are binary; controlling for fixed individual effects requires enough variability within each observations, which is not the case with our data. Also, see the threads discussed by Greene (2004).

In a separate specification, we include a dummy that is equal to 1 if a hurricane (of at least strength 1) hit the locality where the cohort member lived during year *t*. This is done in order to test if experiencing a cyclone has an impact on the probability of attending school and/or being engaged in work. Finally, we also estimate a specification where we introduce the rainfall variable at time *t*-1. This allows us to test for the existence of a lagged effect of rainfall deviation on schooling and working decisions.

One final concern is that economic and social development in a given locality can be systematically correlated with rainfall levels. If this is the case, rainfall might be associated with some unobserved determinants of school and work decisions. To overcome such a possibility: (1) as said earlier, we used rainfall levels normalized to local historical levels, so that high or low rainfall districts in year *t* are defined only with respect to their historical trends and not with respect to other localities (which might be comparatively more rainy); and (2) we run a separate estimation in which we control for localities' fixed effects to test the robustness of our results and to make sure that rainfall deviations are not systematically associated with local development and, so, indirectly related to school and work status.

5. Results

The first set of results reported in Table 4 shows the effect of the continuous standardized rainfall deviation on school and work decisions (Table A.1 provides the results for the full specification). Rainfall deviations positively affect the probability of attending school while they reduce the probability of being engaged in a work activity (column 1). This finding is consistent with what we would hypothesize, given the expected positive effect of good rains on incomes. We cannot disentangle the income from any price effect, which may be affecting the magnitude of the overall effect.

We also note that the effects are heterogeneous across households, which can be seen when we include the interaction of household wealth, at the time the cohort members were 14 to 16 years of age, with rainfall (column 2). This interaction is negative and significant for schooling, and positive for work, suggesting that the effect of rainfall deviation on the decision to attend school or work is attenuated when cohort members are from wealthier households. This finding is consistent with our expectations and points to wealth — and related factors, such as greater access to savings, credit, and insurance — helping to buffer the impact of adverse weather events. This result is also in accordance with Beegle et al. (2006), where assets holding are found to mitigate the (increasing) effects of transitory income shocks on child labour.

Specification 3 further adds the occurrence of cyclones into the model. Like rainfall shocks, cyclones reduce the probability of attending school and appear to push the cohort members into the workplace. We can safely assume that in the case of cyclones, the cohort members are pushed into the workplace and drop out of school as a result of economic hardship, possibly exacerbated by damage to schools and related infrastructure that provides access to educational opportunities.

Specification 4 in Table 4 adds the lagged rainfall and the interaction of the lagged rainfall with 2004 assets. The rainfall and interaction terms are not statistically significant at conventional levels in the schooling model, although the signs of the coefficients are again consistent with our expectations. What is interesting is that the addition of the lagged rainfall variable and the interaction with the asset index does not affect the significance or magnitude of the contemporaneous effect. This corroborates the observation that the impact of current and lagged rainfall events on schooling operate independently of one another. The probability of working is strongly affected by both current and lagged rainfall episodes. The sign, significance, and magnitude of the contemporaneous and lagged effects, are very similar, and this is also applied to the interaction between lagged rainfall and assets.

	(1)	(2)	(3)	(4)
Equation: school				
Rainfall (6 months)	0.057*	0.098**	0.108***	0.110***
	(0.031)	(0.040)	(0.039)	(0.041)
Assets	0.009***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Rainfall x Assets		-0.002*	-0.002*	-0.002*
		(0.001)	(0.001)	(0.001)
Cyclones			-0.237***	-0.388***
			0.096	(0.097)
Lagged rainfall				0.053
				(0.044)
Lagged rainfall x Assets				-0.001
				(0.001)
Equation: work	(1)	(2)	(3)	(4)
Rainfall (6 months)	-0.101**	-0.146***	-0.153***	-0.163***
	(0.040)	(0.047)	(0.047)	(0.045)
Assets	-0.010***	-0.010***	-0.010***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Rainfall x Assets		0.002*	0.002*	0.003**
		(0.001)	(0.001)	(0.001)
Cyclones			0.237*	0.269**
			(-0.130)	(0.132)
Lagged rainfall				-0.175***
				(0.046)
Lagged rainfall x Assets				0.002**
				(0.001)
Observations	8,600	8,600	8,600	8,600

Table 4: Effects of rainfall on school and work decisions, main specifications

Source: Authors' estimation

Notes: specification (1) includes all variables shown in Table A.1 except for the interaction between rainfall and assets; (2) it corresponds to the specification in Table A.1 (this is our base specification); (3) as in (2) plus dummy variable for cyclones; (4) as in (3) plus lagged (t-1) rainfall variable.

In Table 5 we present the marginal effects, based on the specification in the last column in Table 4, to gain insight into the magnitude of the impacts of cyclones and lagged and current rainfall shocks. The occurrence of a cyclone or hurricane decreases the probability of being enrolled in school by 15.2 percentage points and increases the probability of be engaged in a work activity by 10.5 percentage points at mean asset levels. In terms of rainfall, looking at the last column of Table 5, we find that a unit of z-score[17] increase in the standardized rainfall increases the probability of being enrolled in school by 2.5 percentage points (baseline probability 49%) and

[17] Table A.2 provides information on how one unit of z-score translates into absolute mm of rainfall, by climatic zone and nationally.

decreases the probability of being engaged in a work by 4.1 percentage points (baseline probability 52%), calculated at the samples' mean asset levels. Similarly, we find that lagged rainfall increases the probability of work by 5.0 percentage points, slightly higher than contemporaneous rainfall, although the impact on school enrollment is only 1.4 percentage points (that is not, in any case, statistically significant).

	school	**work**	**school**	**work**	**school**	**work**	**school**	**work**
	Assets p25		*Assets p50*		*Assets p75*		*Assets mean*	
lagged rainfall	-0.018	-0.061***	0.015	-0.052***	0.011	-0.041**	0.014	-0.050**
	(0.015)	(0.017)	(0.013)	(0.017)	(0.014)	(0.018)	(0.013)	(0.017)
Rainfall	0.036***	-0.055***	0.027**	-0.044***	0.017	-0.031*	0.025**	-0.041**
	(0.012)	(0.016)	(0.012)	(0.016)	(0.13)	(0.017)	(0.127)	(0.016)
Cyclones	-0.148***	-0.102***	-0.152***	0.105**	-0.153***	0.106**	-0.152***	0.105**
	(0.035)	(0.048)	(0.036)	(0.049)	(0.037)	(0.051)	(0.036)	(0.050)

Table 5: Marginal effects of cyclones, rainfall and lagged rainfall on school and work decisions, at different assets' level

Source: Authors' estimation

We also calculate the marginal effects at different levels of assets to determine the extent to which wealth buffers the impact of rainfall fluctuations. Table 5 shows the point estimates for the 25th, 50th and 75th percentiles of the asset distributions, and Figure 4 plots the curves from the 10th to the 90th percentiles. At the 25th percentile, the impact of a change in one unit of our rainfall measure is a 3.6 percentage point increase in the probability of school, as contrasted with only a 1.7 percentage point increase for cohort members from households at the 75th percentile (for the latter, the effect is even not statistically significant). Similarly, the change in the probability of working associated with a one unit decline in rainfall is to raise the probability of work by 5.5 percentage points for those belonging to the 25th percentile, while for cohort members from households at the 75th percentile, the increase in work probability is almost than half that, 3.1 percentage points. As we get further toward the higher and lower bounds of the asset distribution, we can see that the impact of rainfall shocks on work and school choices are much greater than those for households with less wealth, and conversely, the probabilities of going to school or working is less affected by climate shocks among cohort members from wealth families (Figure 4).

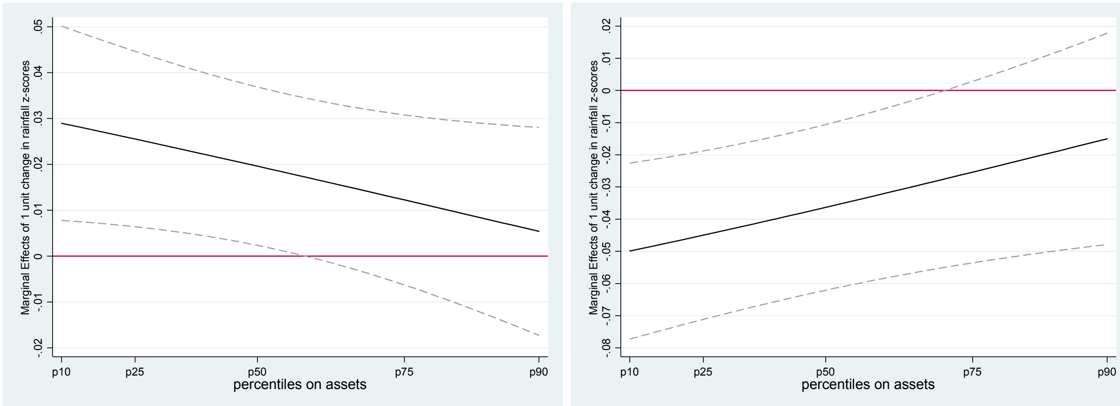

Figure 4: Marginal Effects of rainfall deviations on the likelihood of schooling (left panel) and working (right panel)

Source: authors' estimation based on specification (4) in Table 4.

Notes: dashed grey curves identify the confidence intervals

We next consider several extensions and robustness checks, reported in Table 6. First, we include an interaction with gender (column 5). The negative and significant interaction in the work equation suggests that poor young women in our cohort are even more susceptible to being pushed into the labor market with negative rainfall deviations than male cohort members. When the rains are particularly favorable, however, young women experience a stronger reduction in the probability of being engaged in a work activity.

In another specification (column 6), we exclude from the sample individuals who migrated from the community where they lived in 2004.[18] The reason is that the community variables that we introduced in the model — the presence of schools and the type of land — are from the locality where the individual lived in 2004. When migrants are excluded from the sample, the coefficients are little changed and are of the same magnitude. Also, with such a specification we test whether our results are biased because of the endogeneity of migration decisions, which are possibly also related to rainfalls. According to our results, this does not seem the case, as our estimates are fairly robust irrespective of the sample (with or without migrants) we include.

We also ran a model that excluded from the sample those CMs coming from households who are not engaged in the agricultural sector, which we define as households where none of the members cultivated any land between 2004 and 2011, and where neither the cohort member

[18] We follow individuals in the sample up to the year when they move to another locality. We also estimated the baseline model on the sample of 803 individuals who never changed their residence between 2004 and 2011. Results are stable and are available from the authors upon request.

nor her/his father have reported that their primary sector of work is agriculture. This allows us to check if the rainfall effect could be higher for "agricultural" households. These results, reported in column 7 of Table 6, are stable to the exclusion of non-agricultural households. We can infer from this model that the impact of weather shocks operate, at least in part, indirectly on schooling and work choices, for example, affecting food prices and availability, and more generally, labor market and economic conditions in the rural communities in which the cohort members reside.

	(2)	(5)	(6)	(7)
Equation: school				
Rainfall (6 months)	0.098**	0.093**	0.082*	0.100**
	(0.040)	(0.043)	(0.045)	(0.042)
Assets	0.010***	0.010***	0.008**	0.009**
	(0.003)	(0.003)	(0.004)	(0.004)
Rainfall x Assets	-0.002*	-0.002*	-0.000	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Woman (dummy)		-0.219***		
		(0.065)		
Rainfall x Woman		0.008		
		(0.039)		
Equation: work	(2)	(5)	(6)	(7)
Rainfall (6 months)	-0.146***	-0.111**	-0.136***	-0.133***
	(0.047)	(0.047)	(0.051)	(0.050)
Assets	-0.010***	-0.010***	-0.009***	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
Rainfall x Assets	0.002*	0.002*	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.001)
Woman (dummy)		0.025		
		(0.057)		
Rainfall x Woman		-0.066**		
		(0.034)		
Observations	8,600	8,600	7,355	7,720

Table 6: Effects of rainfall on school and work decisions, robustness checks (sub-population effects)

Source: Authors' estimation

Notes: specification (2) see the note to Table 4; (5) as in (2) plus interaction between rainfall and woman; (6) as in (2) but by excluding migrants (see text for definition); (7) as in (2) but by excluding non-agricultural households (see text for definition)

In Table 7 we run a series of other robustness checks. In specification (8), we estimate the model using localities (communes) fixed effects. Of course, for those CMs who migrated during our period, localities are not constant over time. Both rainfall coefficients are still significant and of a similar magnitude. In the next two robustness checks, shown in Table 7, we employ different definitions of the rainfall variable. We first show, in the specification (9), the results of a model using rainfall measures based on the full year, and not just the rainy season, to define the standardized rainfall deviation. As can be seen, this change does not qualitatively change the results. Specification (10) then reports the results based on a categorical definition of the rainfall deviation: the coefficients are higher as rainfall deviation increases, both for schooling and work. In specification (11), we introduce a dummy variable, instead of the rainfall deviation, to analyze more directly the specific effect of drought. Results show that drought would generate a reduction in the probability of school attendance and an increase in the probability of being engaged in work activities, especially for the poorest cohort members. Finally, specification (12) introduces a seasonality index to assess whether a less even distribution of rainfall over the agricultural season impacts on CMs' school and work decisions. While schooling is not affected by the intra-seasonal distribution of rainfall, a higher concentration of rainfall increases the probability of working, even though, again, assets holding help households to mitigate such a negative effect.

Equation: school	(2)	(8)	(9)	(10)	(11)	(12)
Rainfall categories (ref: <-1)						
Cat2: >-1 & <0				0.517***		
				(0.118)		
Cat3: >0 & <1				0.593***		
				(0.117)		
Cat4: >1 & <2				0.612***		
				(0.134)		
Cat5: >2				0.622**		
				(0.250)		
Assets	0.010***	0.010**	0.009***	0.028***	0.009***	-0.004
	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.011)
Cat2 x Assets				-0.018***		
				(0.005)		
Cat3 x Assets				-0.021***		
				(0.006)		
Cat4 x Assets				-0.015**		
				(0.006)		
Cat5 x Assets				-0.024***		
				(0.008)		
Rainfall (over 12 months)			0.085***			
			(0.031)			
Rainfall (12 months) x Assets			-0.002**			
			(0.001)			
Drought					-0.548***	
					(0.112)	
Drought x Assets					0.019***	
					(0.005)	
Rainfall (6 months)	0.098**	0.086**				0.106***
	(0.040)	(0.041)				(0.040)
Rainfall (6 months) x Assets	-0.002*	-0.002*				-0.003**
	(0.001)	(0.001)				(0.001)

Seasonality Index (SI)						-0.117
						(0.265)
SI x Assets						0.015
						(0.011)
Equation: work	(2)	(8)	(9)	(10)	(11)	(12)
Rainfall categories (ref: <-1)						
Cat2: >-1 & <0				-0.479***		
				(0.166)		
Cat3: >0 & <1				-0.530***		
				(0.172)		
Cat4: >1 & <2				-0.790***		
				(0.212)		
Cat5: >2				-0.714**		
				(0.313)		
Assets	-0.010***	-0.007***	-0.009***	-0.024***	-0.009***	0.007
	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.008)
Cat2 x Assets				0.016**		
				(0.007)		
Cat3 x Assets				0.014*		
				(0.007)		
Cat4 x Assets				0.016**		
				(0.008)		
Cat5 x Assets				0.008		
				(0.011)		
Rainfall (over 12 months)			-0.115***			
			(0.035)			
Rainfall (12 months) x Assets			0.003***			
			(0.001)			
Drought					0.512***	
					(0.169)	
Drought x Assets					-0.015**	
					(0.007)	
Rainfall (6 months)	-0.146***	-0.085*				-0.169***
	(0.047)	(0.046)				(0.049)
Rainfall (6 months) x Assets	0.002*	0.002				0.003**
	(0.001)	(0.001)				(0.001)
Seasonality Index (SI)						0.613***
						(0.239)
SI x Assets						-0.018**
						(0.009)
Observations	8,600	8,600	8,600	8,600	8,600	8,600

Table 7: Effects of rainfall on school and working decisions, with different definitions and measures of rainfall

Source: Authors' estimation

Notes: specification (2) see the note to Table 4; (8) as in (2) plus commune fixed effects; (9) as in (2) but with rainfall estimated over 12 months (instead of over 6 months); (10) as in (2) but with rainfall variable defined in 5 categories (see footnote 19 for their definition) (instead of a continuous rainfall variable); (11) as in (2) but with a binary variable identifying drought (instead of a continuous rainfall variable); (12) as in (2) plus a seasonality index and the interaction between the seasonality index and the assets.

Finally, we acknowledge the concern that individual unobserved heterogeneity may be correlated with our main explanatory variable, rainfall. This would be the case if past rainfall patterns were both correlated with current rainfall patterns and with unobserved individual characteristics. For instance, past unfavorable rainfall patterns could have reduced households' assets or increased their resilience to shocks. If this was the case, what we would observe is not only the effect of current rainfall deviation, but also the possible effect of the long-term pattern of rainfall. We are confident that it is not the case, because we do not use absolute values, but rather a standardized deviation from the long-term mean as the main explanatory variable for rainfall. In addition, our models include many controls, ranging from the lagged wealth index in 2004 in our model to the remoteness index from the early 2000s, as well as employing commune fixed effects. Moreover, as already discussed in Section 3, rainfall deviation is not explained by its lagged value. To further address this concern, as shown in Table A *3*, we have checked if rainfall deviation is correlated with a past rainfall pattern, over the period of analysis. We verified, through a simple regression analysis, that our variable is not explained by the long-term mean of a range of other variables that measure precipitation, including the mean of the same variable, not normalized, and the mean of the variable measuring total precipitation from station data (normalized, and not normalized) during the agricultural season or during the entire year.

6. Conclusion

In this paper, we explore the impact of weather events on school and work decisions of a cohort of young adults in Madagascar. Understanding the human consequences of climate change is particularly important issue in Madagascar, as in other countries, given the evidence that the future will bring more severe cyclones, more frequent droughts and floods and more intra-seasonal rainfall concentration. Further exacerbating the potential deleterious impacts of climate change in such circumstances is the lack of well-established credit and insurance markets, and poverty that limits the ability of household to buffer the impact of negative climate shocks.

Our focus on the impact of weather events on schooling and work is especially pertinent to the cohort of teens and young adults we study, who are transitioning from school to work. The concern is that deleterious shocks will cause young people to drop out of school and enter the labor market to mitigate the impact of drought, floods, and cyclones. A priori, the sign of the impact of rainfall deviations on school and work is undetermined. While a positive increase in rainfall deviation is expected to increase school through an income effect, the sign and the magnitude of the price effect as generated by an increased productivity in the agricultural sector are unknown and heavily depend on the degree of imperfection of markets. To address this question empirically, we estimate a bivariate probit model, using data from 210 localities over the period 2004 to 2011, during which the cohort we examine ages from their teenage years to young adulthood, and controlling for the heterogeneity to vulnerability.

The results of our work provide compelling evidence that negative rainfall deviations and cyclones reduce the probability of attending school and push young men and women into working. Hardest hit are the less wealthy households, as one would expect, given their more limited savings, less access to credit and insurance, and generally more limited ability to cope with negative weather shocks. We also find that there are both contemporaneous and lagged effects of the weather shocks, and that they are of a similar magnitude. Another source of particular concern is that poor young women are even more susceptible to being pushed into the labor market when negative rainfall deviations are experienced. This finding is robust to a range of rainfall definitions. And likewise, we conduct a range of robustness checks, including using community fixed effects and testing for any possible role of individual heterogeneity and correlations with rainfall variability.

The findings in our paper add to a rapidly growing literature on the role of weather shocks on a range of outcomes, including schooling and work, the focus of our paper. While climate scientists will continue to address the causes of weather shocks and work to prevent human activity that contributes to climate change, our research highlights the importance of mitigation efforts. These are especially important for the poor in ecologically fragile countries, like Madagascar, which lack economic and social institutions that can help protect the vulnerable from climate shocks.

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Appendix

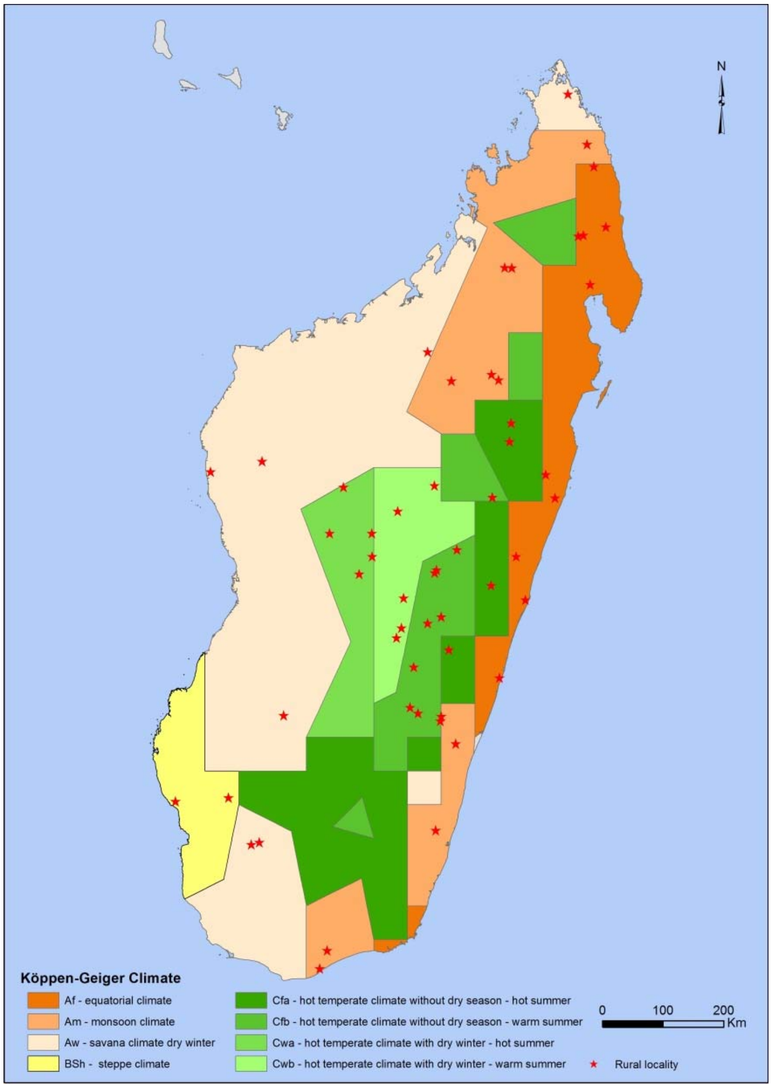

Figure A.1: Climatic zones, Köppen–Geiger climate classification system

Source: Authors' estimation

Notes: 1. Af. Equatorial rainforest, fully humid; 2. Am. Equatorial monsoon; 3. Aw. Equatorial savannah with dry winter; 4. Bsh. Steppe climate (hot steppe); 5. Cfa. Warm temperate, fully humid (hot summer); 6. Cfb. Warm temperate, fully humid (warm summer); 7. Cwa. Warm temperate, dry winter (hot summer); 8. Cwb. Warm temperate, dry winter (warm summer)

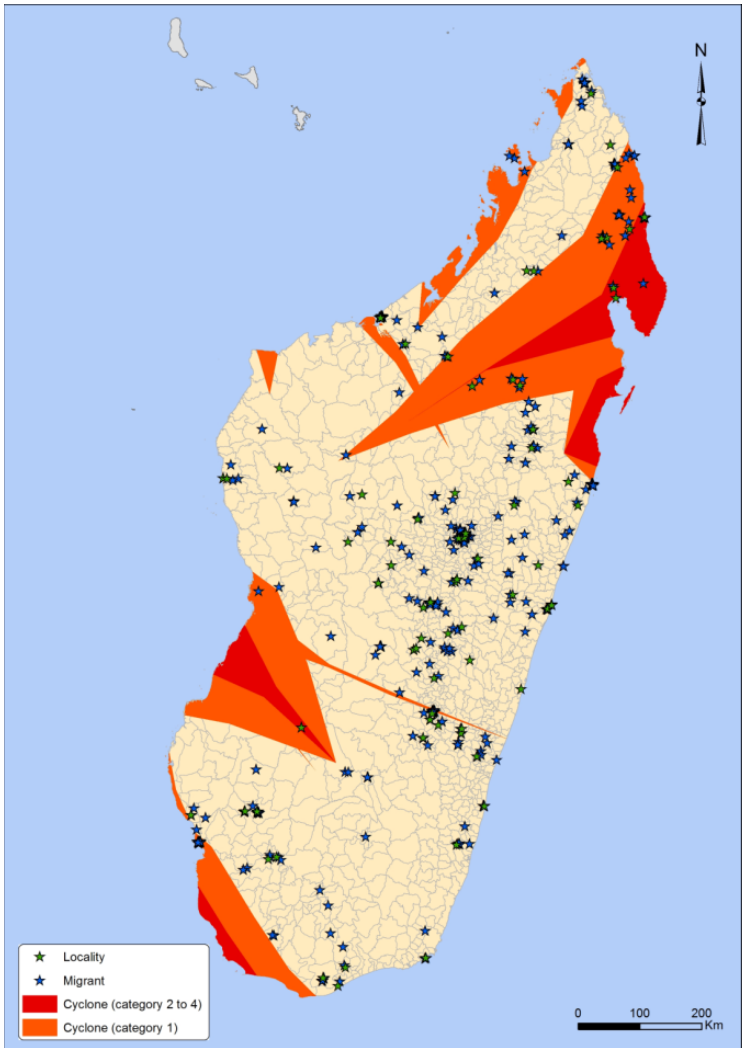

Figure A.2: Cyclones having hit sample communities over the period 2004 to 2012.

Source: Authors' estimations from *Global Risk Data Platform* and *Madagascar Young Adult Survey*

equations	school	work
If CM is a girl	-0.218***	0.015
	(0.065)	(0.057)
Age at school entry	-0.027	0.023
	(0.018)	(0.020)
If CM lives in a new household	-0.289***	0.089
	(0.096)	(0.075)
Number of child siblings, boys	0.002	-0.011
	(0.028)	(0.039)
Number of child siblings, girls	0.010	0.088**
	(0.035)	(0.037)
If father experienced any illness or death	-0.184*	0.104
	(0.103)	(0.123)
If mother experienced any illness or death	-0.125	0.294**
	(0.126)	(0.145)
If father works	-0.129	0.046
	(0.105)	(0.114)
If mother works	-0.026	0.293**
	(0.121)	(0.120)
Number of secondary schools (cycle 1) in the commune	0.181**	0.011
	(0.083)	(0.102)
Number of secondary schools (cycle 2) in the commune	0.099	-0.216*
	(0.083)	(0.131)
If commune has access to a paved road	0.101	0.130
	(0.109)	(0.131)
If the hh had a land in 2004	0.149**	0.125*
	(0.072)	(0.068)
Rainfall deviation (6 months)	0.098**	-0.146***
	(0.040)	(0.047)
Assets in 2004	0.010***	-0.010***
	(0.003)	(0.003)
Rainfall deviation x Assets	-0.002*	0.002*
	(0.001)	(0.001)
Control for (dummies):		
Age of CMs	Yes	Yes
Father's education	Yes	Yes
Mother's education	Yes	Yes
Year (2004 to 2011)	Yes	Yes
Climatic zone	yes	yes
Land type	yes	yes
Athrho	-0.579***	
	(0.058)	
Observations	8,600	

Table A.1: Full specification of the base model

Source: authors' estimation

zone	average	1 z-score	0 z-score
1	1175.389	2166.787	994.8435
2	1070.435	1783.585	964.6864
3	842.5096	1227.292	725.5471
4	510.2336	574.7544	390.2637
5	1113.622	1225.844	979.7858
6	1065.659	1312.056	925.751
7	1321.616	1618.008	1219.17
8	1210.272	1496.411	1074.956
National	1077.534	1423.665	946.4648

Table A.2: Average precipitation (in mm) and precipitation around 1 z-score of rainfall between November and April, national and by climatic zones

Source: authors' estimation

long-term mean of rainfall variables	Coefficient (sd)
Mean of annual precipitation, station data, normalized	-0.0217
	(0.225)
Mean of annual precipitation, station data	-0.000
	(0.000)
Mean of annual precipitation, satellite data	0.000
	(0.000)
Mean of November to April precipitation, station data	0.000
	(0.000)
Mean of November to April precipitation, satellite data	-0.000
	(0.000)
Constant	-0.025
	(-1.118)
Observations	1,533

Table A 3: Effects of the long-term mean of variables measuring precipitation on normalized rainfall deviation.

Notes: Means are calculated over the period 1992-2012