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Abstract*

This paper studies the probability of formally employed men falling into informality because of exposure to hurricanes and tropical storms. It combines destruction variables calculated from historical storms' physical characteristics at the district level with 36 quarterly rounds of labour force surveys in Jamaica. The empirical strategy exploits variation arising from the storms' timing, intensity, and geographic locations within a panel random-effects endogenous choice model framework. Controlling for potential biases due to initial conditions, panel attrition, and employment selection, findings suggest that hurricanes do not affect unemployment and positively affect the transition to informality probability regardless of whether the individual was initially employed in a formal or an informal job. When the marginal effects of the storm were studied, the probability of becoming informally employed ranges between 8.5 and 14.5 percent depending on the employee's initial state and the moment when the storms were suffered. The effect is mainly driven by the impact of hurricanes on the service sector. These results suggest that the public and private policy agenda on adaptation to climate change should incorporate a discussion on how to off-set the negative effects of hurricanes, since these events could become worse in the near future.

JEL classification: C33, E26, J01, J22, Q54.

Key words: Tropical storms, informal employment, labour market transitions, endogeneity, simulated based estimation, Jamaica.

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1 Introduction

The increase in sea water temperatures and levels have become the most important long-term threat to economic development in the Caribbean. The Geophysical Fluid Dynamics Laboratory, a research laboratory in the National Atmospheric and Oceanic Administration's Office of Oceanic and Atmospheric Research, has found that the increase in temperatures will potentially cause worse tropical storms in the future. Their predictions are that the intensity of tropical disturbances will increase between 2 and 11 percent and that the rainfall associated with these events will increase between 10 and 15 percent.[1] These projections imply an increase in the potential socioeconomic effects of hurricanes in the Caribbean region.

The economic damage due to tropical storms is not negligible. Calculations using data from the International Disaster Database (EM-DAT) suggest that the total damage in terms of direct or indirect losses due to these events represents 1 to 44 percent of total annual central government revenue, or a decrease between 0.4 and 9.2 percent of GDP.[2] With this, a potential disruption (due to tropical storms) to the productive sector would be expected. This disruption raises questions about worker's performance under extreme circumstances and adaptation measures that they use to cope with the risks associated with these events.

Are weather shocks affecting the risk that Jamaica's formally employed men become unemployed? If so, is becoming an informal employee a mechanism to smooth consumption? Are men working in the formal sector at risk of falling into informality due to tropical storms in Caribbean economies? These questions are extremely important in developing countries that are annually afflicted by tropical storms or hurricanes. The proposed discussion follows the view of Acevedo (2015), who found that individuals change their behaviour with respect to labour supply to cope with negative effects of weather shocks as an adaptation mechanism for consumption-smoothing purposes. This finding has policy implications.

This paper updates the "new climate economy literature" -Dell et al. (2013)- in two ways. First, it introduces a novel dataset that contains individuals' labour force information in an unbalanced-panel structure interacted with information on tropical storms. These data were collected from original geographic information system (GIS) sources and contain various geographical and physical characteristics of the storms *per se* and of Jamaica's topography. Second, an endogenous switching model is introduced to disentangle causality from tropical storms estimated through maximum likelihood (multivariate probit estimation). This method departs from the standard analysis of environmental shocks that Dell et al. (2013) used to study labour market outcomes, since the methodology proposed herein incorporates a structural analysis of the individual's decision-making process on job options, specifically his decision to become an

[1] https://www.gfdl.noaa.gov/global-warming-and-hurricanes/ visited on September 25, 2017.

[2] Using data from the EM-DAT, the IMF's World Economic Outlook, and the Jamaica central government's budget, I compared the GDP and the central government's revenue in US$ with the estimates from the disaster database between 2001 and 2012.

informal worker. This paper follows the literature to understand the effects of storms on the probability that formally employed individuals fall into unemployment.

To my knowledge, the literature on climate change and economics contains no evidence of how natural disasters affect a man's decision to become informal, an important issue for developing countries. The influence of weather shocks on the allocation of time has been recently studied using exogenous variations in time and geography, principally using rainfall -Acevedo (2015)- or temperature -Zivin and Neidell (2014)- data. These authors find that floods are associated with an increase in unemployment (a result that is more pronounced for women) and a reduction in income from labour. On the other hand, an increase in temperature is associated with a reduction in the labour supply. More related to tropical storms (but with a different approach as presented here) is the work of Belasen and Polachek (2008), who studied how hurricanes affected workers in Florida. They find that hurricanes positively impacted earnings but negatively affected employment. Using data from Mexico, Rodríguez-Oreggia (2013) finds that the potential destruction due to hurricanes as big shocks might increase employment rates, mainly blue-collar jobs involved in reconstruction. Also for Mexico, Spencer and Polachek (2015), using crop production data, find a negative relationship between agricultural productivity and hurricanes that is more pronounced for crops that are above ground. This evidence favours the negative effect of weather shocks on elements of the general equilibrium of labour markets in developing economies. However, I found no study on the effect of weather shocks on transitions in employment formality patterns.

This research also fits within the literature on labour economics. The informal sector has been studied in the Latin American and Caribbean (LAC) region due to its high importance in the region. The effort has been focused on measuring its size using different approaches as mentioned by Alderslade et al. (2006): Electricity consumption -Basbay et al. (2016)-, currency demand -Kamau and Lin (2016)-, night light -Ghosh et al. (2009)-, and micro-data -Gasparini and Tornarolli (2007)-. The intention of this set of studies is to determine the size of the informal sector. However, more research and better data are needed, as stated by Caldera Sánchez et al. (2011). Although attempts have been made to measure the issue, little has been done to identify the individuals that make up the sector or how external factors (like weather shocks) affect their decision to remain in or switch to another employment status. This is interesting since it will provide the necessary evidence to guide the design of public policy to prevent potential switches between statuses or, in the best-case scenario, to help informally employed individuals shift to the formal sector in the advent of negative natural shocks. This paper helps to reduce the gap in the evidence on the effects of negative weather shocks on workers' decisions regarding their formality status as a mechanism to cope with the risk and smooth consumption.

It is important to recognise and understand the source of vulnerability to natural shocks. The study done by Hallagate et al. (2015) points out the importance of protecting vulnerable populations from natural shocks since they lack the formal financial instruments to cope with the risk, specifically, poor people's and/or informal workers' lack of access to financial tools to overcome the negative effects of natural disasters: no access to credit, lack of savings and non-existent formal insurance. The authors claim that this combination of issues and characteristics will create a strong poverty trap due to future weather shocks associated with climate change.

Some research on labour economics has found that becoming an informal employee is a coping mechanism for unemployment. This paper explores how tropical storms affect the probability of moving formal employees to unemployment, since one potential hypothesis for these workers to become informal is that they may prefer to move to a less secure job that generates some income, rather than becoming unemployed. Erasmus (1999) supports this hypothesis, noting that "...those retrenched formal sector workers now start to crowd into the informal sector" referring to the job-creation dynamic in the micro, small, and medium enterprise (MSME) sector. With this, could it be that formal workers that are forced to leave their jobs due to external shocks prefer to become informal workers rather becoming unemployed? This is what could happen in an economy such as Jamaica, given its dependence on the services sector, especially tourism.

This paper estimates the effects of tropical storms on the transition to informality as a coping mechanism to smooth consumption. Its innovation is the use of a wind field model to approximate the actual destruction generated by tropical depressions, tropical storms, and hurricanes in a more precise way than the binary approach, through government reports used in the literature on this class of events.[3] Although the measure does not perfectly correlate with the outcome variable due to imperfect matching at the geographical location of the workers at the time of the event, it is still a good proxy for the destruction as studied by Strobl (2012). It allows the method to exploit a third level of exogenous variation (apart from geography and timing), that is, the intensity of the storm. This information enables the use an endogenous switching model estimated through a multivariate probit to disentangle causality from storms. This model has been tested in other labour market studies, specifically on the characteristics that govern transitions from and to low-wage status, using data from the Great Britain as studied by Cappellari and Jenkins (2006b), and with regard to how informality persistence depends on the status of informality in previous periods, using data from Ukraine as studied by Akay and Khamis (2011). Benchekroun et al. (2014) estimate transition probabilities across sectors using a multivariate logit. This study goes further than Kavuma, Morrissey, and Upward (2015), who studied the transitions to informality using panel data and probit models, since here I control for environmental conditions as negative shocks. It also explores, as a transmission channel, how tropical storms affect employees from the formal services sector, one of the most important sectors in the Jamaican economy.

The importance of this research is based on the size of the informal sector in de-

[3]The proposed method contains more information regarding the storms' physical characteristics unavailable in other research. On the other hand, government's calculations of damages are commonly aggregated at a high geographic level, only available for big hurricanes and unavailable for any other type of disturbance.

veloping economies and its vulnerability to natural shocks. Based on Gasparini and Tornarolli (2007), the informal sector accounted for between 25 (Suriname) and 89 percent (Haiti) of the working population, positioning this issue as one of the greatest challenges in the LAC region. These authors found that informality in Jamaica accounts for 58 percent of the labour force.[4] Some authors have found that, although in different contexts, this population is vulnerable to shocks. The invisibility of this population to public systems worsens their capacity to cope with shocks compared to formal workers. Also, the potential lack of health insurance may imply that the higher costs of accessing good health centres reduces the possibility of this population to receive proper health services, worsening their productivity as mentioned by Perry et al. (2007). Another aspect is lack of access to financing, since in the event of a negative shock, informal workers would not have the means to cope with its effects, forcing them to use their own (usually scarce) savings to do so or even relying financially on family or friends as found by Patankar and Patwardhan (2015).

In terms of public and private action, there is much to be done. From the World Bank's Atlas of Social Protection Indicators of Resilience and Equity (ASPIRE) data, which contains information on coverage of different insurance systems available in the economy, such as for old age, disability, death of the head of household, maternity leave, sickness cash benefits, and social health, it is easy to see that Jamaica is among the bottom three in access to insurance, higher only than Honduras and Guatemala.[5] In terms of health insurance, in a recent paper, Beuermann and Pecha (2016) found that the largest share of the population with private insurance was less than 20 percent and that the implementation of public free access to health care was associated with a significant increase in weekly hours worked, demonstrating that such measures would help workers, otherwise uninsured, to bear negative health shocks. This evidence shows that there is space and a need to improve the public and private sectors' ability to increase the population's coping mechanisms against environmental shocks.

Big storms were found not associated with the risk of falling into unemployment but were found associated with an increase in the probability of falling into informality. This study found that tropical storms did not affect the probability that formally employed individuals would become unemployed. With this, it seems that formal workers have mechanisms to overcome adversity generated by storms, specifically, moving to the informal sector to smooth consumption otherwise harmed by unemployment.

This study found a nonlinear relationship between the storms' accumulated strength and the probability of remaining informal and falling into informality if the individual was initially formally employed. The relationship depicts an exponential pattern

[4]This study uses micro-data to determine the size of the aspect and the most comprehensive study about it has been done using this data -Perry et al. (2007). The World Bank's World Development Indicators shows that informality in the region ranges between 30 percent in Costa Rica and 74.4 percent in Guatemala.

[5]To take a closer look to the data, please refer to
http://datatopics.worldbank.org/aspire/indicator/social-insurance.

where small tropical storms and tropical depressions have almost zero or negative effects; however, when storms pass the threshold defined by hurricanes, the probability associated with the storms' accumulative wind is positive. The probability of remaining informal goes up to 8.5 percent, and the probability of falling into informality when the individual was previously formally employed goes up to 14.5 percent.[6] These findings suggest that there should be a discussion not only on how to protect the informal population but also on how to support the formally employed population so that they do not fall into the informal sector.

The effect is principally driven by the impact of the hurricanes on the tourism sector. The fact that the Jamaican economy is based on tourism and that this sector is severely affected by tropical storms (due to, for example, productive capital destruction, travel restrictions, and coastal degradation) imply that tourism sector employees will confront large smoothing consumption challenges.[7]

This paper presents evidence that the services sector (largely composed of tourism) as a transmission channel of the effect of tropical storms on labour supply dynamics, is the most affected sector in Jamaica. First, the study investigates, using the sample of formally employed men in this sector, how exposure to tropical storms affects the probability of transition to unemployment, where no significant effect was found. Second, it runs estimations of the endogenous switching model using only the same sample and finds that the effect on the probability of transition to informality is positively (and significantly) affected by exposure to hurricanes.

Climate change will increase health shocks and property losses, according to the literature. As mentioned before, Hallagate et al. (2015) underscores the urgency that every economy improves its mechanisms to adapt to the consequences of climate change. The increase in temperatures, the rise in sea level, and the change in crop seasons have created a new global situation threatening the sustainability of life and business as usual. The study also finds that vulnerability to climatic events is negatively correlated with wealth, making developing economies less capable of withstanding increasingly larger natural shocks in contrast with developed economies, where fiscal instruments not designed for risk prevention and reduction, like unemployment insurance and public health provision, are used to mitigate the negative effects of hurricanes, as noted by Deryugina (2016). With this, the poor population, where informal workers are concentrated, will be the most negatively affected by future weather shocks. According to Patankar and Patwardhan (2015), under a flooding shock, informal workers had inadequate coping mechanisms to withstand major flood events in Mumbai.

This paper adds to the evidence on the vulnerability of informal workers to remain

[6]These effects are lower bounds of the true effect, since the relationship between the destruction variable and the actual probability is not perfect.

[7]World Travel and Tourism Council (2017) has calculated that the travel and tourism sector to the Jamaican economy accounted for 30.3 percent of GDP in 2016 and by 2027 will account for nearly 43 percent of GDP. The report is available at https://www.wttc.org/-/media/files/reports/economic-impact-research/countries-2017/jamaica2017.pdf

informal due to big storms, and shows how hurricanes increase the risk that formal workers will fall into informality.

The paper is organised as follows: Section 2 describes the methodology and data used, Section 3 presents the results, and Section 4 concludes.

2 Methodology and Data.

2.1 Methodology: An Econometric Model of Informality Transitions

Following Cappellari and Jenkins (2002) and Cappellari and Jenkins (2006b), the structure of the panel data and the dynamic nature of the analysis present some challenges that the study must tackle. Those challenges are related to response attrition and the initial condition's problem, stated by Heckman (1981b).

The first challenge concerns sample selection via response attrition. I kept only data from men for which I can reconstruct the proxy of formality in period $t-1$ and t since the research question is related to that transition only. This sample of individuals contains men who had information about occupation and those observed in the dataset who did not have the information to construct the occupation. The potential selection to respond to the occupation questionnaire could be not random, so the estimated parameter could be biased.[8]

On the other hand, an individual's status in period t could be affected by his status in period $t-1$, another class of selection bias that could operate in this analysis. The so-called initial conditions problem introduced by Heckman could be at work in this setup in the sense that men in the informal sector could be systematically different than men employed in the formal sector. This systemic difference could imply that the propensity of initially informal people to remain informal is higher than the propensity of the formal ones to become informal.

Finally, a distinction must be drawn between heterogeneity and state dependence. To disentangle participation due to characteristics from state dependence on the observed labour market state's persistence, this study enables the model to account for inter-temporal correlation between unobservable factors in the processes involved - Heckman (1981a). The model also addresses the three challenges through estimation of a four-variate probit model with endogenous selection and endogenous switching.

This study works with a sample of males from Jamaica. This is because information regarding endogenous variables that affect women's decision to work are not available. Let us assume that the sample of men can be seen in a base period, say, period $t-1$. The relevant information is the formality status in that period, so that

[8] I do not take in account potential panel attrition, since the nature of the data set may induce such attrition at random every three to four years due to survey design and master sample's revision. With this, the panel attrition is orthogonal to the individuals' characteristics and/or labour occupation.

only information on workers employed in formal or informal sectors is kept, a common practice in the literature [see Cappellari and Jenkins (2008)].

Following the notation used by Cappellari and Jenkins (2008), for each individual $i = 1, \ldots, n$ in the data from the year $t-1$, I assume that there is a latent informality propensity $I^*_{i,t-1}$, so that observing informal status $I_{i,t-1}$ depends on whether this propensity is larger than a certain observed threshold. The initial conditions equation is defined as:

$$I^*_{i,t-1} = \boldsymbol{\alpha}'\mathbf{x}^{I_{t-1}}_{i,t-1} + u^{I_{t-1}}_{i,t-1}, \text{ where } u^{I_{t-1}}_{i,t-1} = \mu_i + \delta_{i,t-1} \sim N(0,1) \tag{1}$$

$$I_{i,t-1} = \mathbb{1}\{I^*_{i,t-1} > 0\} \tag{2}$$

From equation (1), $\mathbf{x}^{I_{t-1}}_{i,t-1}$ is a vector of individual characteristics and α is the vector of parameters associated to the characteristics. The error term defined by $u^{I_{t-1}}_{i,t-1}$ is the summary of unobserved differences between individuals and are assumed to be uncorrelated with observed characteristics: $u^{I_{t-1}}_{i,t-1}$is the sum of a normal time invariant individual-specific effect μ_i and a normal orthogonal white noise process $\delta_{i,t-1}$. From equation (2), $\mathbb{1}\{I^*_{i,t-1} > 0\}$ is an indicator function that is equal to one if the latent variable is larger than zero, without loss of generality, and zero otherwise.

With the panel nature of the data, assume that in the following period (say, quarter t) there is certain probability of an individual being retained. Again, assume that there is a latent variable $R^*_{i,t}$ that accounts for the propensity of individual i being followed or retained in the data from $t-1$ to t, regardless of the availability of information on status of employment or formality. In the same spirit as the previous set of equations, the observed retention status $R_{i,t}$ depends on the propensity to be non-negative, i.e:

$$R^*_{i,t} = \boldsymbol{\lambda}'\mathbf{x}^{R}_{i,t-1} + u^{R}_{i,t}, \text{ where } u^{R}_{i,t} = \theta_i + \epsilon_{i,t} \sim N(0,1) \tag{3}$$

$$R_{i,t} = \mathbb{1}\{R^*_{i,t} > 0\} \tag{4}$$

The description of equations (3) and (4) is similar to those for equations (1) and (2).[9]

To estimate transition to informality, a second condition must hold. Among the retained sample of men, they must be employed or working in period t in order to observe the information on the state of informality. In the same way as the previous equation on retention, the propensity of being employed or working is given by the latent variable $W^*_{i,t}$ that is a linear function of some characteristics (observed and unobserved) as follows:

$$W^*_{i,t} = \boldsymbol{\gamma}'\mathbf{x}^{W}_{i,t-1} + u^{W}_{i,t}, \text{ where } u^{W}_{i,t} = \omega_i + \eta_{i,t} \sim N(0,1) \tag{5}$$

[9]Note that all the equations are parameterised in terms of base quarter $t-1$'s covariates to avoid simultaneity changes in probabilities and changes in attributes.

$$W_{i,t} = \mathbb{1}\{W^*_{i,t} > 0\} \tag{6}$$

The description of equations (5) and (6) is similar to those of equations (1) and (2). Note that if the individual j was not followed in period t ($R_{i,t} = 0$), equation (5) is truncated.

Lastly, the transition equation that describes the informality status in period t is presented. Let us assume that the propensity of being informal in period t is described by the latent variable $I^*_{i,t}$ characterised by a linear index specification of base period characteristics but conditioned by the base period informality status, the so-called endogenous switching regression:

$$I^*_{i,t} = [\boldsymbol{\beta}'_1 I_{i,t-1} + \boldsymbol{\beta}'_2(1 - I_{i,t-1})]\mathbf{x}^{I_t}_{i,t-1} + \sum_{\tau=1}^{2}[\boldsymbol{\varphi}'_{1,\tau} I_{i,t-1} + \boldsymbol{\varphi}'_{2,\tau}(1 - I_{i,t-1})]\mathbf{S}_{d,t,\tau} + u^{I_t}_{i,t}, \tag{7}$$

where

$$u^{I_t}_{i,t} = \nu_i + \pi_{i,t} \sim N(0,1)$$

$$I_{i,t} = \mathbb{1}\{I^*_{i,t} > 0\} \tag{8}$$

Equation (7) contains the central point of the research. As can be seen, the transition equation is a linear function of some characteristics in base year ($\mathbf{x}^{I_t}_{i,t-1}$) and the storms suffered at the district d level in quarter $\tau = 1, 2$ before last interview. With this, the set of parameters $\varphi_{1,\tau}$ indicates the effect of tropical storms suffered $\tau = 1, 2$ quarters before interview in period t conditional on being informal in the base period on the probability of being informal in period t.[10] The correspondent description for $\varphi_{2,\tau}$ is the effect of tropical storms suffered during $\tau = 1, 2$ quarters before interview in period t conditional on being formal in the base period on the probability of being informal in period t, that is, the parameter of interest. Note that this equation is truncated for the cases $E_{i,t} = 0$ or $R_{i,t} = 0$ (not working in period t or not retained in the panel, respectively)

Figure (1) depicts the chain, or sequence, of events. From the data, I kept only men who were either working in either the informal or the formal sector in the base period. With this, individuals are either $I_{t-1} = 1$ or $I_{t-1} = 0$. One of the hypotheses behind the use of the endogenous model is that the panel retention could be not random and that the formality status may affect the probability of being observed in the following round. With this, in the second level of the Tree, individuals can be followed in period t or not. In the case that an individual cannot be followed, the only information available is for the informality state in $t-1$ and the information for the retention (since the covariates in the equation form retention are located in $t-1$).

[10]Note that all the equations are parameterised in terms of base quarter $t-1$'s covariates in order to avoid simultaneity changes in probabilities and changes in attributes.

Attrition can be defined from two sources. One important aspect to note is that there could be two different means of attrition: either an individual cannot be followed or, if followed, the information regarding employment status is missing. In both cases the non-followed and the missing in response are treated as not retained, $R_t = 0$.

On the other hand, when $R_t = 1$, the working state in t is observable. For the period t I kept all those individuals who were working in the formal or the informal sector as well as the unemployed. At this point, a second truncation of the information is present since all of those that are observed as unemployed do not have information about the employment sector. If the individual is $W_t = 1$, it is possible to observe the informality state in t. Each of these groups contributes to the general likelihood of being informal in t.

The sample is divided depending on the realisations of the variables R_t, E_t, I_t, as described in Figure (1), these realizations are the expression of three different sets of individuals in the sample that will contribute in the way expressed in (1).

In this study, I will keep all those individuals that in $t-1$ were either informal or formal employees. Also, the retention will be equal to 1 if the individual can be followed from $t-1$ and t; however, if an individual is observed in t and its working or employment status is observed but not the sector (variable $I_{i,t}$ is missing), it will be part of the non-retained individuals (i.e $R_{i,t} = 0$).

Let us assume that the set of unobservables are jointly distributed as:

$$(u^{I_{t-1}}_{i,t-1}, u^R_{i,t}, u^W_{i,t}, u^{I_t}_{i,t}) \sim \mathcal{N}_4(\mathbf{0}, \mathbf{\Sigma}) \tag{9}$$

That is a four-variate normal distribution with means of zeros and variance-covariance matrix $\mathbf{\Sigma}$The advantage of having such an exogenous variation coming from the tropical storms allows me to adopt a random-effects specification since the unobserved heterogeneity of the individual is orthogonal to the distribution of the storms, in which the elements off diagonal of the variance-covariance matrix are the cross-equation covariance components of the time invariant individual-specific effects (μ_i, θ_i, ω_i, ν_i).

With the four-variate normal distribution assumption, the individual contribution to the likelihood in each group of table 1 is given by:

$$\begin{aligned}
\mathcal{L}_{A_i} &= \Phi_2(k_{1,i}\boldsymbol{\alpha}'\mathbf{x}^I_{i,t-1}, k_{2,i}\boldsymbol{\lambda}'\mathbf{x}^R_{i,t-1}; \rho_1) \\
\mathcal{L}_{B_i} &= \Phi_3(k_{1,i}\boldsymbol{\alpha}'\mathbf{x}^I_{i,t-1}, k_{2,i}\boldsymbol{\lambda}'\mathbf{x}^R_{i,t-1}, k_{3,i}\boldsymbol{\gamma}'\mathbf{x}^W_{i,t-1}; \rho_1, \rho_2, \rho_3) \\
\mathcal{L}_{C_i} &= \Phi_4(I_{i,t-1}\Psi_{1,i} + F_{i,t-1}\Psi_{2,i}; \rho_1, \rho_2, \rho_3, \rho_4, \rho_5, \rho_6), \text{ where } F_{i,t-1} = 1 - I_{i,t-1}
\end{aligned} \tag{10}$$

where Φ_n is the n^th-variate normal cumulative density function,

$$\Psi_{1,i} = (k_{1,i}\boldsymbol{\alpha}'\mathbf{x}^{I_{t-1}}_{i,t-1}, k_{2,i}\boldsymbol{\lambda}'\mathbf{x}^R_{i,t-1}, k_{3,i}\boldsymbol{\gamma}'\mathbf{x}^W_{i,t-1}, k_{4,i}\Big[\boldsymbol{\beta}'_1\mathbf{x}^{I_t}_{i,t-1} + \sum_{\tau=1}^{2}\boldsymbol{\varphi}'_{1,\tau}\mathbf{S}_{d,t,\tau}\Big])$$

and

$$\Psi_{2,i} = (k_{1,i}\boldsymbol{\alpha}'\mathbf{x}^{I_{t-1}}_{i,t-1}, k_{2,i}\boldsymbol{\lambda}'\mathbf{x}^R_{i,t-1}, k_{3,i}\boldsymbol{\gamma}'\mathbf{x}^W_{i,t-1}, k_{4,i}\Big[\boldsymbol{\beta}'_2\mathbf{x}^{I_t}_{i,t-1} + \sum_{\tau=1}^{2}\boldsymbol{\varphi}'_{2,\tau}\mathbf{S}_{d,t,\tau}\Big])$$

Note the change in the subindex of $\boldsymbol{\beta}$. Let us define k as the sign of i's contribution as $k_{1,i} = 2I_{i,t-1} - 1$, $k_{2,i} = 2R_{i,t} - 1$, $k_{3,i} = 2E_{i,t} - 1$, and $k_{4,i} = 2I_{i,t} - 1$.

For the estimations, I will use a quadratic version of the storm variable. In the next section, I explain how to construct the destruction variable that will account for all the physical information regarding the storms' $S_{d,t,\tau}$ variable. The idea of using a second-degree polynomial expression of the form of the destruction variable is to capture the effect of the level of the storm's strength that will inform, if the storm increases in power, how it will affect the transition probability (low level of destruction/wind versus high level). With this, the storm variables for the expressions in $\Psi_{1,i}$ and $\Psi_{2,i}$ become:

$$\sum_{\tau=1}^{2} \boldsymbol{\varphi}'_{1,\tau}\mathbf{S}_{d,t,\tau} = \sum_{\tau=1}^{2}[\varphi_{1,1,\tau}S_{d,t,\tau} + \varphi_{1,2,\tau}S^2_{d,t,\tau}] \tag{11}$$

and

$$\sum_{\tau=1}^{2} \boldsymbol{\varphi}'_{2,\tau}\mathbf{S}_{d,t,\tau} = \sum_{\tau=1}^{2}[\varphi_{2,1,\tau}S_{d,t,\tau} + \varphi_{2,2,\tau}S^2_{d,t,\tau}] \tag{12}$$

respectively.

The interpretation of the storms' parameters is as follows. If $\varphi_{1,1,\tau}$ is positive (negative), small storms affect positively (negatively) the probability of become informal in the second stage given that the individual's initial status was informal. If $\varphi_{1,2,\tau}$ is positive (negative), big storms affect positively (negatively) the probability of become informal in the second stage given that the individual's initial status was informal. If $\varphi_{2,1,\tau}$ is positive (negative), small storms affect positively (negatively) the probability of become informal in the second stage given that the individual's initial status was formal. If $\varphi_{1,2,\tau}$ is positive (negative), big storms affect positively (negatively) the probability of become informal in the second stage given that the individual's initial status was formal.

In the other hand, the covariances ρ_j are defined as:

$$\begin{aligned}
\rho_1 \equiv &\quad corr(u^I_{i,t-1}, u^R_{i,t}) = cov(\mu_i, \theta_i) \\
\rho_2 \equiv &\quad corr(u^I_{i,t-1}, u^W_{i,t}) = cov(\mu_i, \omega_i) \\
\rho_3 \equiv &\quad corr(u^R_{i,t}, u^W_{i,t}) = cov(\theta_i, \omega_i) \\
\rho_4 \equiv &\quad corr(u^I_{i,t-1}, u^I_{i,t}) = cov(\mu_i, \nu_i) \\
\rho_5 \equiv &\quad corr(u^R_{i,t}, u^I_{i,t}) = cov(\theta_i, \nu_i) \\
\rho_6 \equiv &\quad corr(u^W_{i,t}, u^I_{i,t}) = cov(\omega_i, \nu_i)
\end{aligned} \tag{13}$$

With these, the distribution of unobserved heterogeneity is parameterised through the cross-equation correlations. Correlation ρ_1 describes the association between unobservable individual-specific characteristics that determine the base year informality status and the panel and employment retention. A positive (negative) sign indicates that individuals who are likely to be informal in the base year are more (less) likely to be retained in the following survey compared to formal individuals. The ρ_2 describes the relationship between initial informality and the individual's employment likelihood in the following period. A positive (negative) sign indicates that informal individuals are more (less) likely to be employed in the following period compared to formal ones. The ρ_3 describes the relationship between retention and employment state. A positive (negative) sign indicates that retained individuals are more (less) likely to be or to become employees compared to those who were not retained.

An important correlation to see is ρ_4. It describes the relationship between unobservable characteristics of individuals who were informal workers in the base year and those for informal individuals in the following period. As expected, a positive sign means that initially informal workers were more likely to remain informal in the following observed period, and the contrary for a negative sign. For the least two, the definition operates in the same way as in the first two.

With these components, a four-variate probit model can be defined to estimate the transition probabilities and their components. Combining the equations from equation (10), a derivation of the log-likelihood contribution for any man i is represented by:

$$\log(\mathcal{L}_i) = (1 - R_{i,t}) \log(\mathcal{L}_{A_i}) + R_{i,t}(1 - W_{i,t}) \log(\mathcal{L}_{B_i}) + R_{i,t} W_{i,t} \log(\mathcal{L}_{C_i}) \tag{14}$$

These elements ask for two important conditions. On the one hand, an exogenous restriction must be in place for identification purposes. In a model with no conditional cross-equation correlations, it is important to declare regressors that are relevant for the endogenous equations that are at the same time conditioning the informality process. They will be discussed in the data section.

A valuable feature of the cross-equation correlation is the possibility of identifying ignorable conditions. To test the ignorability of each selection mechanism, I test if the correlations between equations are jointly not significant. If $\rho_1 = \rho_2 = \rho_4 = 0$ the initial conditions equation can be ignored from the estimation. If the case is that $\rho_1 = \rho_3 = \rho_5 = 0$, retention is ignorable and, finally, if $\rho_2 = \rho_3 = \rho_6 = 0$, the employment condition can be ignored.

To estimate the model, I used simulated maximum likelihood. I base the estimation exercise on the routines designed by Cappellari and Jenkins (2006a) to calculate multivariate normal probabilities by simulation generating a code that accounts for the likelihood function described in equation (14). The result of equation (14) is what Cappellari and Jenkins (2008) call "partial likelihood" (or "pseudolikelihood") since there is a violation of the standard assumption of independence of the error term across observations. The data consist of repeated observations of the same men across successive pairs of quarters, since I paired couples of quarters from the LFS panel data. With this, I used clustering of the error term at the individual level to adjust the variance-covariance matrix, since in this way arbitrary correlations between observations of the same individual can be allowed.

2.2 The Effects of Tropical Storms on the Services Sector: A Transmission Channel Exploration

The literature on labour economics describes evidence of the negative impacts of weather shocks on employment. The present study addresses the effect of tropical storms on unemployment, using a simple regression approach of the following form:

$$U_{i,t} = \boldsymbol{\alpha}'\mathbf{x}_{i,t-1} + \sum_{\tau=1}^{2} \boldsymbol{\upsilon_{\tau}}\mathbf{S}_{d,t,\tau} + \delta + \theta + \lambda + \epsilon_{d,t} \tag{15}$$

where $U_{i,t}$ is a dummy variable that takes a value 1 if men i was formal in period $t-1$ and unemployed in period t and zero if the individual remains formal across periods. $\mathbf{x}_{i,t-1}$ is a vector of individual and districts' characteristics and δ , θ, and λ are district, time, and linear trend fixed effects to control for any unobservable characteristics that are constant at the regional level across time, and any technological change that could affect the probability of unemployment and the normal error term is defined by $\epsilon_{d,t}$. The parameters of interest are defined in vector $\boldsymbol{\upsilon_{\tau}}$ since these will measure the effect of the nonlinear model of exposure to tropical storms on unemployment. The intention with this approach is to understand if weather shocks affect how formal workers move out of employment or remain formal.

2.3 Data

2.3.1 Labour Force Survey of Jamaica

The dataset comes from two different sources. The first is the Jamaica Labour Force Survey (LFS) for the years 2004 to 2014 with some gaps. This survey is representative at the rural and urban level, at the parish (the largest geographical division), and at the national level. The LFS is implemented quarterly and is a rotational panel on dwellings.

The LFS has a two-stage stratified random sample design. In the first stage, a selection of primary sampling units (PSUs) is made, and in the second stage there is a selection of dwellings. A PSU is an enumeration district (ED) or a combination of EDs that is selected for a sample usually defined by the previous census. The ED division is the third level of geographic desegregation where the second is constituency and the first is parish. After the random selection of PSUs, a list of the dwellings located in each PSU is executed to define the master sample for the LFS. Each ED contains a minimum of approximately 100 dwellings in rural areas and a minimum of 150 dwellings in urban communities. After the EDs are selected, a list of dwellings is created; this list is the master sample. This master sample is revised every three to four years (for representativeness purposes).

The LFS is by nature a rotational panel on dwellings. Once the selected PSUs are listed, 32 dwellings are randomly selected from each PSU. These 32 dwellings are then divided into eight groups, or panels, of four dwellings each. Dwellings in panels

1 to 4 are interviewed in the first quarter LFS (16 dwellings per PSU each quarter). Dwellings in panels 3 to 6 are interviewed in the second quarter LFS. Dwellings in panels 5 to 8 are interviewed in the third quarter LFS. Dwellings in panels 1, 2, 7, and 8 are interviewed in the fourth quarter LFS. In the first quarter of the following year, dwellings in panels 1 to 4 are interviewed again and the yearly cycle is repeated (Table 2). This rotating panel scheme with the same dwellings lasts until the master sample is revised usually every three to four years.

From these data, I kept individual characteristics and formality status for men for whom the time elapsed between observations is three to four quarters. I selected this sample for two reasons: on one hand, variables that could affect the labour endogenous choice for women, such as fertility, are not available, making it hard to test the hypothesis on this population. On the other, a three to four quarters time frame will increase the chances of having storms in between and reacting to them between observations. The set of variables used as controls contains individual characteristics like age, education, occupation (a dummy=1 if individual has a professional occupation, zero otherwise), and geographic location (a dummy=1 if individual lives in rural area, zero for urban) in others. To create a proxy for informality, that is, the main outcome variable, I used the information provided by workers in two ways.[11] The first, the National Insurance Scheme Criteria, define a worker as informal if he satisfies any of the following conditions:

- Declares himself as employee of the private sector and carries out his job at his family dwelling; or
- Employee of the private sector and carries out his job at a family dwelling or plantation, garden, farm, employer's house, and the number of people working in the business is two to nine; or
- Employee of the private sector and carries out his job at family dwelling or plantation, garden, farm, and the number of people working in the business is four to nine; or
- Employee of the private sector and carries out his job at family dwelling or plantation, garden, farm, employer's house, industry, factory, office, and the number of people working in the business is five or six.

The second, called firm registration criteria, defines an employer as informal if he satisfies any of the following conditions:

- Declares himself as self-employed and carries out his job at family dwelling; or

[11] In 2015, the Statistics Office of Jamaica, with the support of the Inter-American Development Bank, implemented a special survey on informality using a sample from the LFS. The conditions presented here to create the variable for informality characterise the respondents in this survey. The data are not available for public use; the information to build the informality dummy from the LFS was provided for this study.

- Self-employed worker and the number of people working in the business is two and he carries out his job at a plantation, garden, farm; or
- Self-employed worker and the number of people working in the business is three and he carries out his job at employer's house; or
- Self-employed worker and the number of people working in the business is one and he carries out his job at an industry, factory, house; or
- Self-employed worker and the number of people working in the business is two to four and he carries out his job at construction site; or
- Self-employed worker and the number of people working in the business is one and carries out his job on the street in a fixed location; or
- Self-employed worker and the number of people working in the business is one to two and he carries out his job on the street with no fixed location; or
- Self-employed worker and the number of people working in the business is one to two and carries out his job at a shop or store; or
- Self-employed worker and the number of people working in the business is one to two and carries out his job at a market or stall.

With the informality variable, an instrument for equation (1) is needed. One of Heckman's recommendations throughout his work is to use information from the time prior to the individual's working life as instrument for initial conditions equations. This kind of information, like the parent's labour history or their economic status when he was a child, is not available in this survey. With the data available, I used as an instrument for equation (1) a variable that contains the working status in the past five years. The effect of this variable to the transition probability is through its effect on the initial conditions equation, which at the same time affects the probability of being employed in the following period. The instruments used in equations (3) and (5) of retention and working probabilities are discussed in the following section.

2.3.2 Empirical average transition probabilities form Labour Force Survey of Jamaica

After describing the dataset, I present a table that describes the average transition probabilities. Table 3 presents the transition probabilities for the sample used and, as can be seen, there are changes after accounting for the different sources of potential attrition bias (unemployment and panel attrition). I also take into consideration the possibility of item non-response as in Cappellari and Jenkins (2008). However, the sample under this condition is negligible since out of the final 109365 observatios used in the estimation, fewer than 0.01 percent did not respond. With this, I define the attrition group to be filled by all those men that do not have a follow-up and those with item non-response.

It seems that attrition is not random in this sample. As can be seen in panel (a), the probability of being informal in the follow-up period is almost 7 times higher for those that were informal in the base period (68.9 versus 11.2).[12] In panel (b), the large share of unemployed in the follow-up period was informal in the base period. In this case, the sample used was not only individuals that have information on informality in the follow-up period, but also those who became unemployed.

Lastly, panel (c) incorporates the sample that cannot be followed due to attrition. The sample in this category is particularly large for men who were informal in the base period. These descriptions of the transition probabilities show that the attrition of the sample in not necessarily negligible. However, this research will shed light if including this factor in the analysis affects men's decision making on labour supply.

2.3.3 Storms and Geographical Data.

Data used for tropical storms is extracted from the International Best Track Archive for Climate Stewardship (IBTrACS) from the National Oceanic and Atmospheric Administration (NOAA). This dataset contains information on every tropical storm between 1969 and 2014, including date, trajectory, maximum sustained wind, radius of maximum speed, minimum central pressure (mb), and others. This information is collected every six hours for the storm's lifespan and is used to build the wind field model that is basic for destruction index calculations. Figure 2 shows the tracks and wind speed (in scale of thickness) for the set of storms used. Table 6 lists information regarding the dates of each storm, the maximum wind speed, and the category of the storm (Saffir-Simpson scale).

Following the discussion on identification of the endogenous equations, I use geographic characteristics to instrument retention and working probabilities. I use as an instrument for working probability in equation (5) the elevation of the district with respect to the sea level, and as instrument for the retention equation I use the linear distance between the geographic district's centroid and Kingston. Some evidence in the survey design and labour economics -(Antonovics et al. (2000) ; Lall and Mengistae (2005), respectively- have found that geographic factors such as distance to the nearest urban centre and the topographical characteristics of the firms' region affect largely the probability of attrition to surveys when panel data are at work and the working probabilities and specialisation of the locations, respectively. With this, the distance to Kingston will affect the probability of being followed in the panel, and through this it will affect the probability of being employed and the transition probability but not the initial conditions. On the other hand, elevation would affect the probability of being employed, and through this, the transition probability but not the retention probability or the initial conditions.

[12]This paper is not intended to identify the degree of persistence or heterogeneity of state dependence. This will be left for future research.

2.3.4 Wind Filed Model and Storm Destruction Variable.

Following Strobl (2012) and Boose et al. (2004), the destruction variable built for Jamaica contains an approximation of the storm's local wind speed in every district on the island. Boose et al. (2004) tested the method using data from Puerto Rico, an island 700 miles east of Jamaica. Due to the proximity of these two countries and their similarities in terms of location and vulnerability to tropical storms, it is possible to use estimated parameters from the abovementioned authors. The wind field model is the application of the Holland (1980) equation for cyclostrophic wind and sustained wind speed.

$$V_{d,s,r} = GF\left[V_m - S(1-\sin(T))\frac{V_h}{2}\right]\left[\left(\frac{R_m}{R}\right)^B \exp\left(1-\left[\frac{R_m}{R}\right]^B\right)\right]^{1/2} \tag{16}$$

$V_{d,s,r}$ is the estimate of the s storm's wind speed at some district d at some point in the storm's life, r. V_m is the maximum sustained wind velocity that storm s reaches at any point, T is the clock-wise angle between the storm's forward path and the ray between the storm's center, and the centroid of district d, V_h is the forward storm's speed, R_m is the radius of maximum winds, R is the length of the ray that connects the storm's center and the district's centroid d, G is the gust factor, finally F, S and B are surface friction, asymmetry due to forward motion of the storm, and the shape of the wind profile curve, scaling parameters estimated by Strobl (2012) and Boose et al. (2004) for some Caribbean islands. Figure 3 depict the relationship between the abovementioned variables. The information on the total wind received by a specific district is contained in the variable given by:

$$WIND_{d,s} = \int_t^{\tau} V_{d,s,r}^{3.8} dr \tag{17}$$

where $WIND_{d,s}$ is the destruction variable estimated for the district's centroid d and it is equal to the summation of the values of wind field to the a power of the storm s' lifespan. The GIS data contain an observation for each tropical storm every six hours, so that, for each one of them, I estimate the wind field model $V_{d,s,r}$ for storms that are between 0 and 310 miles from the closest district as depicted in Figure 2.[13] The 3.8th power depicts the relationship found by Strobl (2012) between total costs due to hurricanes and the maximum observed wind speeds. Figure 4 shows an example using hurricane Ivan's destruction proxy. In the figure, districts with red values suffer large destruction due to wind and less destructive values correspond to districts with orange coloring, finally, the black line represents the hurricane's track. For the estimation purposes, I defined a new index of exposure which values goes

[13]As mentioned in Strobl (2012), this assumption relies on the fact major storms can reach a diameter of more than 600 miles.

between 0 and 100 and represents the percentage of storm's exposure with respect of the maximum exposure observed in the data set.[14]

In terms of the estimation, the variable called S in equations (11) and (12) are filled with $WIND_{d,s}$ and the its square. The process is as follows:

Step 1. Using man i's quarter of survey (D_i^b) and the date of storm's observation (D_s) I know if he was hit one or two quarters before the observation in period t as follows

1. If $D_s - D_i^b \in [-3, 0]$ months, man was hit one quarter before last observation t.
2. If $D_s - D_i^b \in [-6, -4]$ months, man was hit two quarters before last observation t.

With these criteria I can define dummy variables, one per period of interest.

Step 2. The dummies crated above have a value of 1 if a storm s hit man i in quarter q. To create the treatment as the total shock received by man i in period q, the corresponding destruction index for storm was multiplied s times the dummy corresponding to man i quarter q. This procedure creates treatment variables with values corresponding to the destruction indexes in each position where the dummies have value equals to 1. Finally, we add all the values over quarter q by each man i since more than one storm may hit during the same quarter.

Figure 5 contains a graphic example of the variation in time I am exploiting. The first column depicts the quarter for which there are data available from LFS. In the second column, a dummy that informs the availability of storm in each quarter that tells about the storms suffered one or two quarters before the last interview. After that, the quarter/LFS panel implemented is in green, and the period in which the storm is located between rounds is in red. Take as example panels C and D in 2005q2. This sample is affected by storms between observations that are three or four quarters apart. The same analysis holds for panels E, F, G, and H. The advantage of the sample comprising panels A and B is that it is like a control group that did not suffer from storms between rounds. This structure defines the sample used to estimate the endogenous choice model.

[14]The rescaling procedure was to create the following variable :

$$\text{New index}_d = \frac{Wind_{d,s} - \min(Wind_{d,s})}{\max(Wind_{d,s}) - \min(Wind_{d,s})} = \frac{Wind_{d,s}}{\max(Wind_{d,s})}$$

where $\max(Wind_{d,s})$ and $\min(Wind_{d,s})$ are the maximum and minimum of the observed distribution of exposure and in particular $\min(Wind_{d,s}) = 0$.

3 Results

3.1 Results from the Estimation of the Four-variate Probit

3.1.1 Ignorability Tests

One of the aims of the endogenous choice model is to account for potential selection and to determine whether there is a relationship in non-observables between decisions. From Table 4, the only non-observable correlations that are different from zero are the ones between retention in the panel and being informal in $t-1$ and the one for informal in t and working probability in t. However, this result does not indicate ignorability of conditioning decisions.

To define ignorability, the null hypothesis of correlation equal to zero should be rejected. As can be seen, the only selection equation that can be ignored from the analysis is retention.

3.2 The Effects of Tropical Storms on Transition Probabilities

Table 5 presents the results of the effect of storms on the probability of transitioning to informality. In the first column, I present the parameter from the four-variate probit estimation and their correspondent standard errors, and the second column lists the values under the naïve univariate probit that were estimated for comparison purposes. The four-variate model fits the observed transitions well, since for the initially formally employed individuals, the predicted probability of falling into informality is similar to the one calculated in panel (a) in Table 3, as it is for those individuals who were initially informally employed. In terms of estimated parameters, the effect of the storms on the transition probability has a U-shape. This means that beyond a certain threshold, the probability of become informal is positive on the exposure to the storm, disregarding the initial status. The regression includes controls and instruments described in the previous section, and the parameter estimations can be found in the Annex.[15] One important aspect to keep in mind after comparing the naïve versus the four-variate model is that the naïve model overestimates the parameter for storms in almost all cases. This is related to the potential bias suffered by this estimation.

As noted by Stewart and Swaffield (1999), Cappellari and Jenkins (2008), Mullahy (2015), and Mullahy (2016), it is difficult to compute marginal effects for this class of models. The complication arises from the correlation across equations that makes it

[15] As technical note, I estimated the model using the *mvnp* from Cappellari and Jenkins (2006a) with 373 simulations that is the square root of the total sample used (109,356), that is the amount of simulations recommended by the authors to optimise the simulations. I used a Stata 14 MP with 4 cores in a Mac Book Pro with intel i7 processor of 2.5Ghz. I adapted the plugin designed by professor Jenkins for Macintosh due that it was not available for this platform and only restricted to Windows. You can download the c++ file for plugin and the plugin from my webpage: https://sites.google.com/site/camilopechag/home/research/stata-files.

possible for one variable to affect not only the equation that is modelled initially, but also other equations for which the first one is conditioning. The method used here is the one proposed by Mullahy (2016), based on the following formula that is the derivative of the four-variate normal distribution with respect to storm s:

$$\frac{\partial \Phi_4(I_{i,t-1}\Psi_{1,i} + F_{i,t-1}\Psi_{2,i}; \widehat{\rho}_1, \widehat{\rho}_2, \widehat{\rho}_3, \widehat{\rho}_4, \widehat{\rho}_6, \widehat{\rho}_6)}{\partial S_{d,t,1}} =$$

$$\phi(I_{i,t-1}(k_{4,i}\left[\widehat{\boldsymbol{\beta}}_1' \mathbf{x}_{i,t-1}^{I_t} + \sum_{\tau=1}^{2} \widehat{\boldsymbol{\varphi}}_{1,\tau}' \mathbf{S}_{d,t,\tau}\right]) + F_{i,t-1}(k_{4,i}\left[\widehat{\boldsymbol{\beta}}_2' \mathbf{x}_{i,t-1}^{I_t} + \sum_{\tau=1}^{2} \widehat{\boldsymbol{\varphi}}_{2,\tau}' \mathbf{S}_{d,t,\tau}\right]))\times$$

$$\Phi_3(I_{i,t-1}\Psi_{1,i}^{-I_t} + F_{i,t-1}^{-I_t}\Psi_{2,i}; \widehat{\rho}_1, \widehat{\rho}_2, \widehat{\rho}_3)\times$$

$$\widehat{\varphi_{1,1,1}} + 2\widehat{\varphi_{1,2,1}} S_{d,t,1} \tag{18}$$

This equation computes the individual marginal effect of the storms experienced one quarter before the last observed period by men that were informal in $t-1$. The same process applies for the other three sets of parameters (equation (10)). As can be seen, it is used as input for the estimation from the four-variate probit and the covariates to calculate the derivative.

As mentioned before, there is a U-shaped relationship between the exposure to storms and the transition probability to informality. When I evaluated the marginal effect at the mean of the observed exposure to storm vector, the average effect of the storm was negative and significant, although small. To better understand what could be the implications of increase in power of the storm I graph the average individual marginal effect evaluated on different values of the destruction variable. [16]

As can be seen in Figures 8 and 6, the main positive effect comes from the destruction generated by mainly large shocks. In both cases, when individuals' initial state is informal or formal, there is a threshold around 35 percent of the maximum exposure observed where the probability of falling into informality becomes positive.[17] Compared with the values that non-hurricane storms generate, hurricanes are mainly responsible for this finding.

The effect of tropical storms and hurricanes on transition probability to informality is not negligible. The study of the results from the graphs shows that for exposures to

[16] The figure evaluates the marginal effect at each value of the exposure to tropical storms. In the case of a normal OLS, the procedure is to compute $\hat{\beta} \cdot x_i$ but in the present case, this multiplication is given by the derivative of the four-variate normal distribution function with respect to the storm defined in equation 17 multiplied by the storm variable. I only used 10 data points belonging to the upper bound of each decile of the destruction variable's distribution. This was done this way since the estimation of the individual marginal effect at each point requires the simulation of the four-variate normal distribution, so that the computation of every data point in the data set would requires nearly to a year of computing time, per variable.

[17] In these data, the destruction before 30 percent is attributed exclusively to tropical depressions and tropical storms. After 30 percent, the destruction is attributed almost exclusively to hurricanes since the measure of destruction takes in account the destruction/wind received in each quarter by the district's centroid.

storms above 50 percent of the largest registered in the sample have an impact between 1 and 14.4 percent in the transition probability for initially formal employees. The effect is statically significant; however, the confidence interval expands at the limit due to the small sample under maximum exposure.

The potential magnitude of destruction generated by hurricanes is broadly known. These kinds of events are among the greatest catastrophes that economies can suffer. There is evidence worldwide of losses in infrastructure: roads buried under landslides due to heavy rainfall, bridges destroyed due to the intensity of rain and wind, buildings such as hospitals and schools destroyed, shoreline and costal line covered with debris due to wind gusts, food production reduced due to the destruction of tall crops such maize and rice, and assets prices increased due to scarcity are some of the results of this class of events (http://www.desinventar.org). The evidence found in these pages is related to a general equilibrium effect, where all these conditions could push workers into informality if they were formal or induce them to remain informal, specifically in the services/tourism sector.

The method of testing for transmission channels is not straightforward. This study has found that, on average, the effect of big storms is negative. The increase in storms' destructive power will move workers from the formal sector into informality, and this should have heterogeneous magnitude with respect to the sector in which the man was initially employed. Coastal economies commonly depend on services, such as tourism, that could be directly affected if infrastructure is not suitable to receive new visitors. Another potentially affected sector is agriculture, since these kinds of shocks could imply moving people from the rural formal sector to the informal sector. Although there are no data available to test this transmission channel, a study on the heterogeneous effect by sector is needed, not only to understand the actual channels but also to encourage better targeting and design of private and public policy.

Climate change is generating conditions for worse storms to spawn. Although there is no consensus, it is true that the rise in the sea water level and temperature will help increase storms' strength and destructive power so that increasing its effect on various aspects of social welfare as the labour situation. These conditions and the increase in temperatures worldwide will create big losses in national economies, as Carleton and Hsiang (2016) predict.

3.3 Back-of-the-Envelope Analysis

To understand an economic impact of this transition I am presenting a quantification of the losses on contributions to the social security system (National Insurance System, NIS, and National Housing Trust, NHT) in Jamaica. The NIS is "...a compulsory contributory-funded social security scheme, which offers financial protection to workers and their families against loss of income arising from injury on the job, incapacity, retirement, or death of the insured."[18] The NHT is a contribution to the system that

[18]Extracted from the definition provided by the Ministry of Labour and Social Security of Jamaica (http://www.mlss.gov.jm/pub/index.php?artid=20) on November 1, 2017.

provides grant access to housing solutions in the country (improve infrastructure and financial assistance).

The NHT is a contribution to the system that provides grant access to housing solutions in the country (improve infrastructure and financial assistance).[19] Using data from the 2014 Labour Force Survey, I found that the reduction on these contributions is around 6 percent of the total, assuming maximum exposure to tropical storms and 14 percent of formal employees move to informality. On the other hand, a reduction of contributors to the NHT of 14 percent would make it impossible to grant financing for housing to almost 1,100 individuals per year. These economic costs require a policy discussion on ways to help employees remain in the formal sector.[20]

3.4 The Effect of Tropical Storms on Unemployment

Consideirng the transmission channel of how tropical storms affect labour supply decision I studied the sector that is most vulnerable economic sector to weather shocks: the services sector. This sector suffers from the impact of tropical storms in different ways: the increasing intensity of bad weather conditions impacts negatively the number of people traveling to the island; the destruction of infrastructure due to wind or heavy precipatation limits the supply of tourism services; coastal erosion due to wind gusts reduces agricultural yield, among others.[21] These vulnerabilities shrink the demand for labour in the aftermath of a natural disaster; thus, men employed in the services sector risk becoming unemployed.

Men formally working in the services sector prefer to become informal before becoming unemployed in the aftermath of tropical storms. The results of the model defined in equation (15) show that tropical storms do not affect the probability that formal employees in the services sector will become unemployed. I implemented the four-variate model for this sample and found that the positive effect on the probability of transition to informality is statistically significant.[22] These findings confirm that the sector's vulnerability to natural disasters is latent and that this could harm the economy in two ways: first, the decline in economic revenues due to disruption of the sector's normal functioning, and second, a reduction in income tax revenue due to the transition to workers to informality following a natural disaster.

[19] The amount in Jamaican dollars is JAD$1'500,000 using a 2017 exchange rate of JAD$128.9 per US$ 1.

[20] The calculations are the following: The total revenew calculated by 2014 from contributions to NIS and NHT is JAD$42.9 million. Out of these, 55.5 percent (JAD$21.4 million) corresponds to contributions to the NHT for which the total individuals serviced by 2014 was 7,802. With this, a reduction of 14 percent in revenues expected by the NTH will represent a decrease of 1,092 individuals serviced. On the other hand, the reduction of 14 percent of contributors to the NIS represents a reduction of 6.2 percent of total revenue. Data on NHT was obtained from the National Housing Trust (http://www.nht.gov.jm/sites/default/files/Final_Annual_Report_to_Cabinet_October_9.2015.pdf) consulted on November 1, 2017.

[21] For more insights in this regard, please refer to Donovan and Mycoo (2016).

[22] I implemented the four-variate model in other sectors, such as agriculture, but I found no effect. This could be because the sector is predominantly informal.

4 Conclusion

In this paper, I used an endogenous choice model to determine the causal effect of storms on the probability of transitioning to informality. The study uses data from a labour force survey of Jamaica and geographical and physical information from 35 storms (13 tropical depressions, 11 tropical storms, and 11 hurricanes) between 2004 and 2014. I interacted a measure for the total amount of destruction generated by a set of storms that affected the district with the men reported in the Labour Force Survey in that district. I created a pseudo panel of individuals due to the nature of the survey to describe the transition probabilities between the formal and informal sectors to informality across time. The main question was, do tropical storms affect the probability of transitioning to informality? The identification strategy relies on the exogenous variation at the geographic, time, and strength of the events, with which I estimated a four-variate probit to control for three potential biases: initial conditions, panel attrition, and employment selection.

I found that, regardless of the initial state of being a formal or an informal worker, the effect of tropical storms on the probability of transitioning to informality is positive. An advantage provided by the dataset is that it enables testing of how the effect behaves as the accumulated power derived from tropical storms increases. The estimation results show that as the accumulated amount of destruction derived from the storms suffered during one to two quarters between observations increases, the probability of remaining informal across periods varies between 1 and 11 percent, particularly due to hurricanes. The proper probability for those men that start from a formal job varies between 1 and 12 percent. This model also controls for education, age, and occupation. The findings contrast with those of Bosch and Maloney (2010), who find that informality is a voluntary state, since these exogenous events can be seen as pressure for workers to move, involuntarily, to informality. It is important to note that the results obtained are lower bounds of the potential effects, since the correlation between the actual location of the individual at the moment of the event is not perfectly correlated with the destruction variable; however, it is the better approximation at the moment.

Lack of information may still bias the results. Although the estimation through structural modelling eliminates most of the potential selection bias, measurement error could harm the result in two ways. First, I built the informality variable based on the Institute of Statistics' definition for the year 2014 and trace back on time using individual characteristics the potential informality status. As of now, it is not possible to actually observe the informal status in terms of contributions to the National Insurance Scheme and this could downward bias the estimation. Second, since I do not have the exact location where the individual was exposed to storms, the approximation of the storms' variable using districts' centroid as the location of exposure to all the individuals living in a particular district would downward bias the estimation. These two are data problems that cannot be fixed at this moment, however the accuracy on informality can be refined in the future since the survey of the labour force will contain a module exclusive for informal individuals.

The results are average storms, effects on working men. Potential heterogeneity can be present in the initial state-industrial sector, since the services sector might behave differently than the agricultural sector, for example. This study is still open and will also shed light on the actual transmission channel since, at the moment, it appears that the effect found is a general equilibrium effect where a certain part of the demand or inputs used by the labour market are affected by the storms. However, at this point there is no data to test this possibility.

The evidence found represents a step further in our understanding of the potential effects of climate change. Jamaica, as a small-island developing state, is threatened by the rise in the sea level and temperature fluctuation, important factors in increasing the intensity of tropical storms. As described by NOAA:

> Anthropogenic warming by the end of the twenty-first century will likely cause tropical cyclones globally to be more intense on average. This change would imply an even larger percentage increase in the destructive potential per storm, assuming no reduction in storm size.[23]

With this, the danger caused by increasingly worse storms calls for new policies on adaptability and resilience.

In terms of coping tools for workers who bear the greatest risks due to environmental shocks, a discussion on prevention must take place. According to the literature, the most important instrument available to businesses to cope with negative environmental shocks is preparation. McDonald et al. (2014) study shows how preventive measures, formal financial instruments, and informal insurance are used as mechanisms to mitigate and adapt to the effects of hurricanes. They found that the most effective mechanisms to cope with the negative effects of strong hurricanes are preparedness and formal financial instruments. They also found that informal insurance (financial help from friends and family, household resources, etc.) has no effect on offsetting the negative impact of hurricanes on businesses. They implement a bivariate probit estimation, controlling for bias that could arise from business demise. The evidence found in this paper and in the literature can help stimulate a discussion on the instruments that the public and private sector should create to help the population overcome negative shocks.

As mentioned by Hallagate et al. (2015), the informal population is badly equipped to bear with environmental shocks. These authors, and others like Boccanfuso and Savard (2011), show that workers in the informal sector are younger, with lower levels of educational attainment, and poorer than those in the formal sector. With this, understanding of the potential effects of climate shocks, access to insurance and financial instruments are low, making them more vulnerable and prone to fail in entrepreneurship endeavors. Thus, falling into informality or remaining in it is not only an economic issue but a welfare issue, because the productive system deteriorates

[23] Geophysical Fluid Dynamic Laboratory. https://www.gfdl.noaa.gov/global-warming-and-hurricanes/ Visited on November 28, 2016

and sources of income become harder to find, as noted by Acevedo (2015) in the Colombian case. This analysis also follows findings by Carter et al. (2007) who show that natural disasters like droughts and hurricanes can push people into poverty, since mechanisms to overcome the negative effects of such events are not available for this population.

The results add to the actual barriers to job formalisation. As mentioned in FORLAC (2014), the most important barriers found in Jamaica (which also probably exist in most developing economies) are "...low economic growth with low employment generation, tax incentives that give priority to capital-intensive projects, sustained public spending adjustment policies, and low institutional capacity to promote and monitor compliance with labour standards or promote formality in employment." (FORLAC (2014); 1). With this, and few resources to confront natural disasters, informal labour in the economy could become stagnant and impossible to remove.

The results found are not definitive and need more research. Although considerable efforts were made to gather and harmonise data for this study, computational constraints prevented deeper exploration. There are two main potential ways to expand this research: first, it is necessary to expand the number of states of employment studied; this study only looked at informal and formal, leaving out of the analysis the unemployed and those who are out of the labour force. However, expansion of the state space requires more instrumental variables to identify all the equations that will be interacting in the multivariate probit, as well as more computational power, since the simulation required for the estimation grows exponentially with the number of equations used in the model.

The second way to expand the research is the heterogeneous effect. It is extremely important to determine whether there are any differences in how industrial sectors are affected by tropical storms, for example in terms of the loss of productive forces, and what switches workers make because of the storms.

Finally, from a macro perspective, Deryugina (2016) poses a new question regarding the fiscal instruments used to compensate for the negative effects of tropical storms. In this case, it would be interesting to study whether the implementation of free access to public health in Jamaica would imply a reduction in the potential negative effects in health due to storms. It would also be interesting to understand how other fiscal instruments, like the national insurance scheme, react to tropical storms. More household data from other Caribbean economies are needed to explore the external validity of these estimations.

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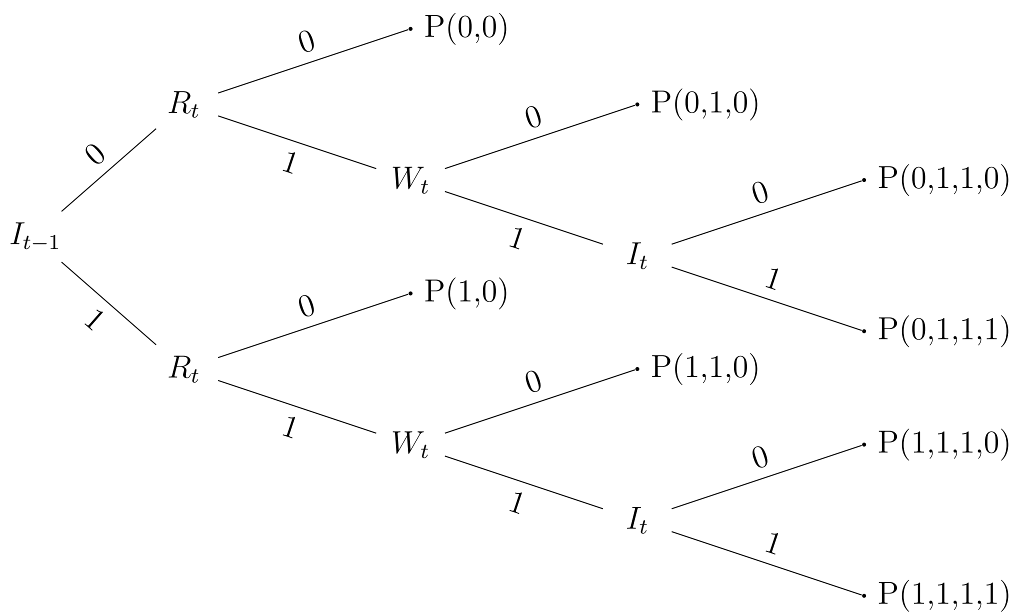
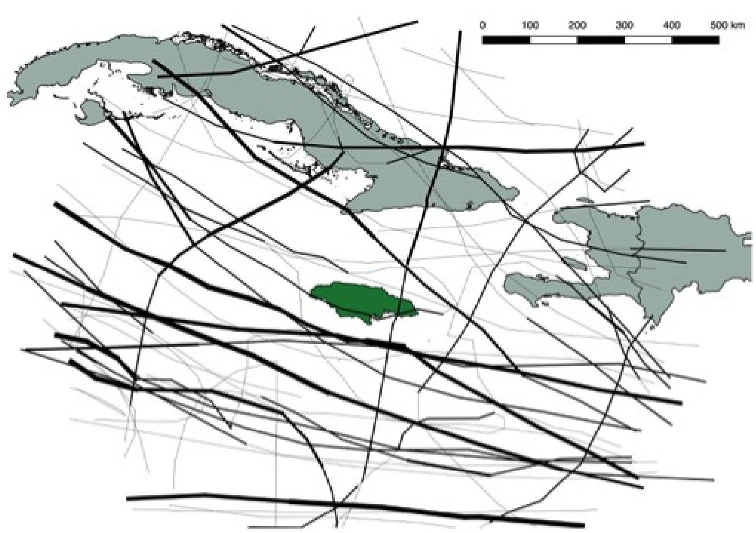
5 Figures and Tables

Figure 1: Chain of events.



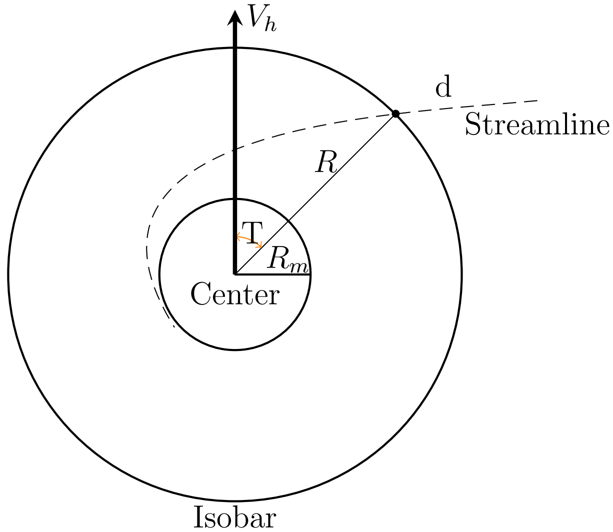
Source: Author's elaboration based on potential events between two periods of employability

Figure 2: Set of storms used



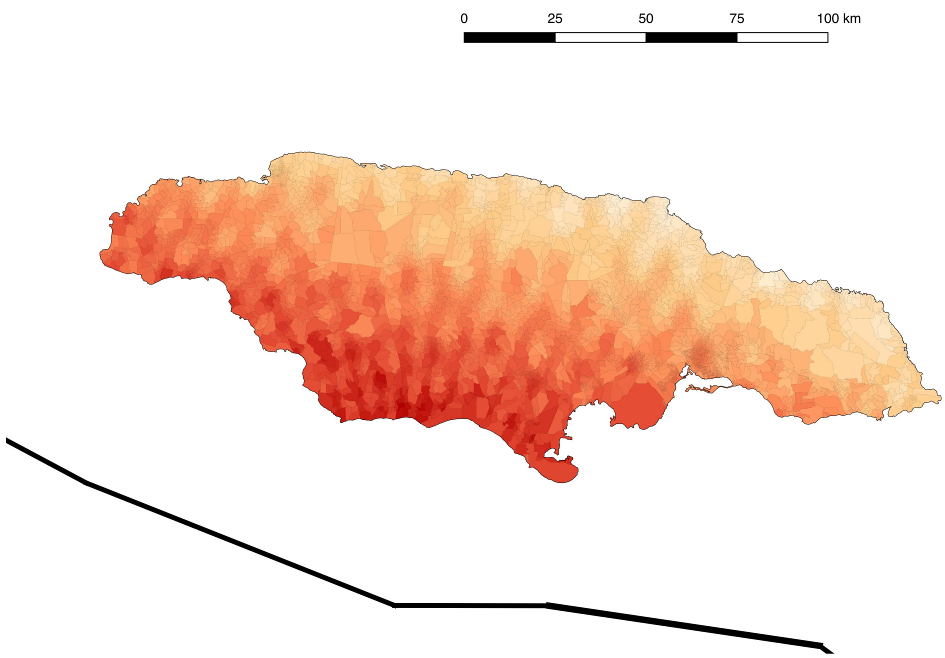
Source: ib-TrACS-NOAA 2004 to 2014. Author's calculations.

Figure 3: Wind field model structure based on Boose et al. (2004)



Source: Boose et al. (2004)

Figure 4: The destruction variable generated by Hurricane Ivan in 2004



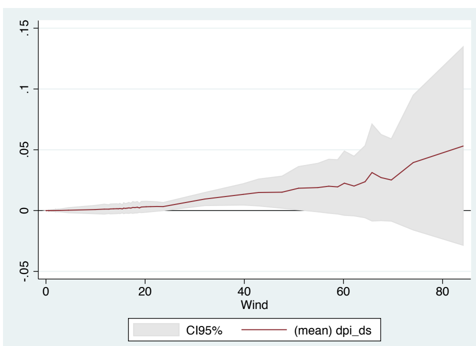
Source: Author's calculations using data from ib-TrACS-NOAA.

Figure 5: Sample of estimation

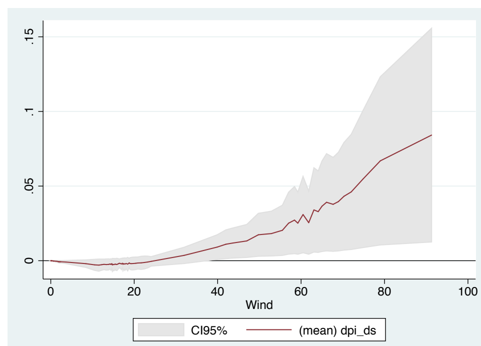
Quarter	Storm 1Q or 2Q before last interview (1/0)	Panels Surveyed in LFS A	B	C	D	E	F	G	H
2005q1	0								
2005q2	0								
2005q3	0								
2005q4	1								
2006q1	1								
2006q2	0								
2006q3	0								

Source: Labor Force Survey of Jamaica

Figure 6: Marginal effects for informal to informal probability evaluated at different storms' values



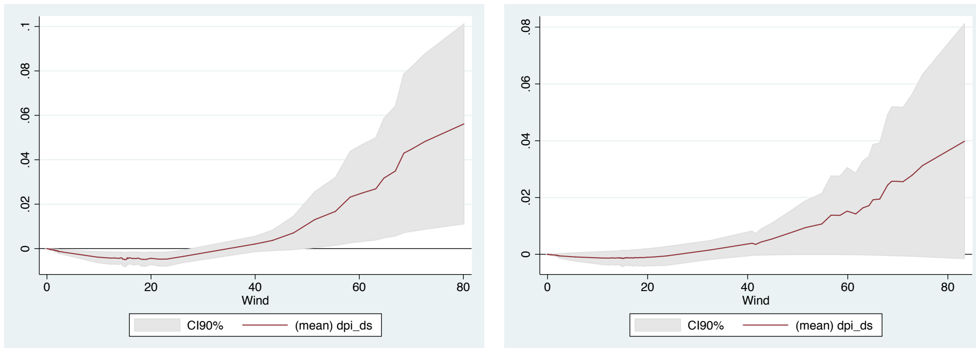
(a) Marginal effect of storms one quarter before t



(b) Marginal effect of storms two quarters before t

Note: the line represents the average individual marginal effect at each centile estimated after the four-variate model. 95% Confidence intervals in gray. Standard error is clustered at the district level

Figure 7: Marginal effects for formal to informal probability evaluated at different storms' values

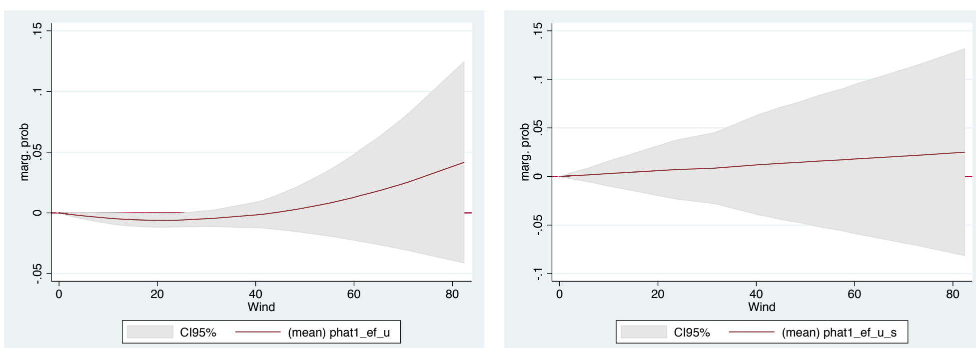


(a) Marginal effect of storms one quarter before t

(b) Marginal effect of storms two quarters before t

Note: the line represents the average individual marginal effect at each centile estimated after the four-variate model. 95% Confidence intervals in gray. Standard error is clustered at the district level

Figure 8: Marginal effect for formal to unemployment probability evaluated at different storms' values

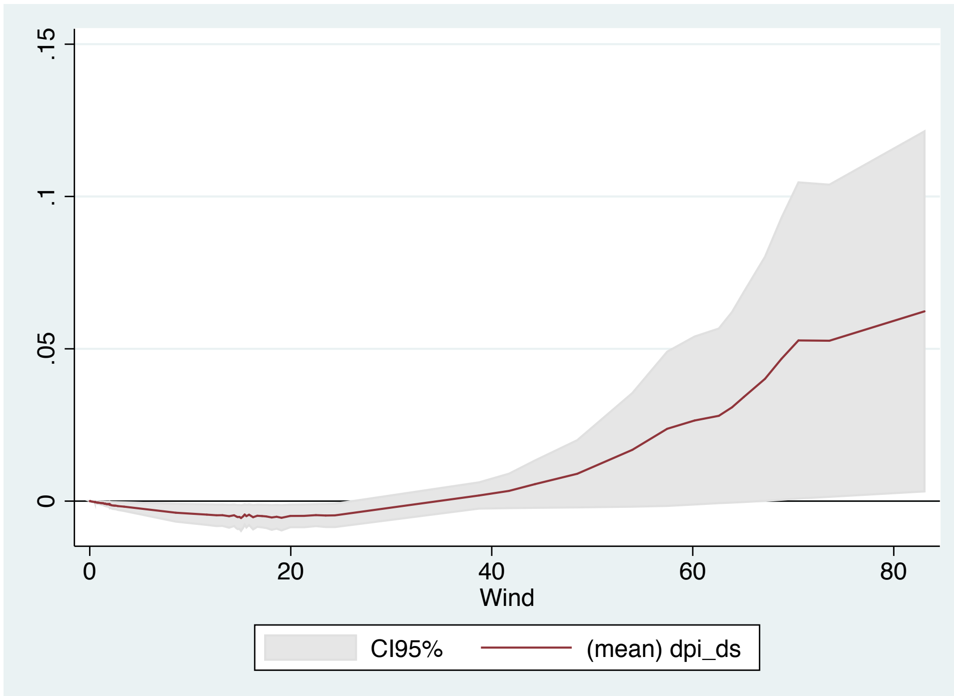


(a) Marginal effect using complete sample

(b) Marginal effect using services sample

Note: the line represents the average individual marginal effect at each centile estimated after the four-variate model. 95% Confidence intervals in gray. Standard error is clustered at the district level

Figure 9: Marginal effects for formal to informal probability evaluated at different storms' values using services sample (Effect one quarter before)



Note: the line represents the average individual marginal effect at each centile estimated after the four-variate model. 95% Confidence intervals in gray. Standard error is clustered at the district level

Table 1: Likelihood contribution groups based on Cappellari and Jenkins (2008).

Group	Retention	Working	Informal	Interpretation
A	$R_{i,t} = 0$	No observed	Not observed	Panel attrtition
B	$R_{i,t} = 1$	$W_{i,t} = 0$	Not observed	Retained, unemployed
C	$R_{i,t} = 1$	$W_{i,t} = 1$	$I_{i,t} = 0$	Retained, formal employee
	$R_{i,t} = 1$	$W_{i,t} = 1$	$I_{i,t} = 1$	Retained, informal employee

Table 2: LFS rotational panel

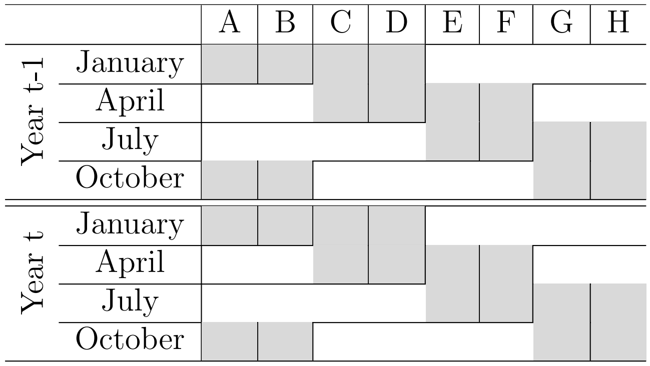


Table 3: Empirical average informal job transition probabilities for Jamaican men.

Year $t-1$ State	Year t state (row %) Formal Group C	Informal Group C	Unemployed Group B	Attrition Group A
(a) Panel with $t-1$ and t information on informality (N=116644)				
Formal	87.4	12.6		
Informal	23.5	76.5		
All	68.9	31.1		
(b) Accounting for and missing information (N=130844)				
Formal	77.6	11.2	11.2	
Informal	21.2	68.9	9.9	
All	61.5	27.7	10.9	
(c) Accounting for and missing information (N=177804)				
Formal	57.4	8.3	8.3	26
Informal	15.4	50	7.2	27.4
All	45.2	20.4	8	26.4

Groups A, B, and C were defined in Table 1. The data used was the quarterly Labor Force Survey (with gaps) for between 2004 and 2014.

Table 4: Ignorability tests

Correlation of unobservables	Parameter	Estimate	SE
Retention, Informal at $t-1$	ρ_1	-0.01	0.04
Working at t, Informal at $t-1$	ρ_2	-0.15***	0.02
Working at t, Retention	ρ_3	0.02	0.17
Informal in t, Informal at $t-1$	ρ_4	0.02	0.17
Informal in t, Retention	ρ_5	-0.01	0.04
Informal in t, Working in t	ρ_6	-0.42	0.72
Ignorability tests	χ^2	p-values	
Initial conditions $H_0 : \rho_1 = \rho_2 = \rho_4 = 0$	88.61	0.000	
Panel retention $H_0 : \rho_1 = \rho_3 = \rho_5 = 0$	0.15	0.9857	
Working $H_0 : \rho_2 = \rho_3 = \rho_6 = 0$	94.35	0.000	
Unobserved heterogeneity $H_0 : \rho_1 = \rho_2 = \rho_3 = \rho_4 = \rho_5 = \rho_6 = 0$	96.38	0.000	

Table 5: Transition probabilities for Jamaican men: Estimated parameters and average individual marginal effect from four-variate probit

	$P(I_{t=1}\|I_{t-1} = 1)$		$P(I_{t=1}\|F_{t-1} = 1)$	
	4-V Probit	Univariate Probit	4-V Probit	Univariate Probit
Predicted probability	0.78	0.71	0.11	0.09
Storm 1 Quarter before	-9.84E-04	8.05E-04	-6.18E-03	-4.42E-03
SE	2.93E-03	2.85E-03	2.63E-03	2.55E-03
Storm 1 Quarter before (sqr)	4.57E-05	2.46E-05	9.50E-05	6.53E-05
SE	4.54E-05	4.41E-05	4.09E-05	3.99E-05
Storm 2 Quarter before	-2.76E-03	-3.79E-03	-1.95E-03	-1.45E-03
SE	2.21E-03	2.11E-03	1.99E-03	2.04E-03
Storm 2 Quarter before (sqr)	5.55E-05	5.92E-05	4.56E-05	3.21E-05
SE	3.41E-05	3.34E-05	2.89E-05	3.02E-05
Observations	109356	109356	109356	109356

The four-variate probit estimation also uses dummies for year apart from the variables described in section 2.3. Standard errors in parentheses were clustered at the individual level as described in the methodology section. * $p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Appendices

Table 6: Set of storms

Year	Storm	Max wind speed (Km/h)	Start date (near to Jamaica)	End date (near to Jamaica)	Saffir-Simpson Scale
2004	BONNIE	55	3-Aug-04	13-Aug-04	T D
2004	CHARLEY	130	9-Aug-04	15-Aug-04	SS 1
2004	IVAN	145	2-Sep-04	24-Sep-04	SS 1
2004	JEANNE	105	13-Sep-04	29-Sep-04	T S
2005	ALPHA	45	22-Oct-05	24-Oct-05	T D
2005	DENNIS	130	4-Jul-05	18-Jul-05	SS 1
2005	EMILY	140	11-Jul-05	21-Jul-05	SS 1
2005	GAMMA	45	14-Nov-05	21-Nov-05	T D
2005	WILMA	160	15-Oct-05	26-Oct-05	SS 2
2006	CHRIS	55	1-Aug-06	6-Aug-06	T D
2006	ERNESTO	75	24-Aug-06	4-Sep-06	T S
2007	DEAN	150	13-Aug-07	22-Aug-07	SS 1
2007	FELIX	150	31-Aug-07	6-Sep-07	SS 1
2007	NOEL	75	24-Oct-07	5-Nov-07	T S
2007	OLGA	50	10-Dec-07	16-Dec-07	T D
2008	FAY	60	15-Aug-08	28-Aug-08	T D
2008	GUSTAV	135	25-Aug-08	5-Sep-08	SS 1
2008	HANNA	75	28-Aug-08	8-Sep-08	T S
2008	IKE	125	1-Sep-08	15-Sep-08	SS 1
2008	PALOMA	125	5-Nov-08	14-Nov-08	SS 1
2010	ALEX	95	24-Jun-10	1-Jul-10	T S
2010	BONNIE	40	22-Jul-10	25-Jul-10	T D
2010	KARL	110	13-Sep-10	18-Sep-10	T S
2010	MATTHEW	50	23-Sep-10	26-Sep-10	T D
2010	NICOLE	40	28-Sep-10	30-Sep-10	T D
2010	RICHARD	85	19-Oct-10	26-Oct-10	T S
2010	TOMAS	85	29-Oct-10	10-Nov-10	T S
2011	EMILY	45	2-Aug-11	7-Aug-11	T D
2011	RINA	100	22-Oct-11	29-Oct-11	T S
2012	ERNESTO	75	1-Aug-12	10-Aug-12	T S
2012	HELENE	50	9-Aug-12	18-Aug-12	T D
2012	ISAAC	70	20-Aug-12	1-Sep-12	T S

Continued on next page

Table 6 – continued from previous page

Year	Storm	Max wind speed (Km/h)	Start date (near to Jamaica)	End date (near to Jamaica)	Saffir-Simpson Scale
2012	SANDY	100	21-Oct-12	31-Oct-12	T S
2013	DORIAN	50	31-Jul-13	31-Jul-13	TD
2014	HANNA	35	25-Oct-14	26-Oct-14	TD

Table 7: Estimation results

	P(Informal_{t-1})		P(Retention)		P(working_t)		P(Informal_t—Informal_{t-1})		P(Informal_t—Formal_{t-1})	
Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
T_1Q_as1_t							-9.84E-04	2.93E-03	-6.18E-03	2.63E-03
T_1Q_as2_t							4.57E-05	4.54E-05	9.50E-05	4.09E-05
T_2Q_as1_t							-2.76E-03	2.21E-03	-1.95E-03	1.99E-03
T_2Q_as2_t							5.55E-05	3.41E-05	4.56E-05	2.89E-05
T_1Q_as1_t_1	-2.50E-03	1.76E-03	2.95E-03	4.81E-03	-2.92E-03	2.04E-03				
T_1Q_as2_t_1	4.01E-05	2.75E-05	-3.44E-05	7.55E-05	5.93E-05	2.94E-05				
T_2Q_as1_t_1	-2.28E-03	1.96E-03	1.92E-03	5.14E-03	-5.37E-03	2.15E-03				
T_2Q_as2_t_1	3.46E-05	2.91E-05	-4.41E-05	6.92E-05	5.94E-05	3.25E-05				
rural_t_1	0.45	0.04	-0.19	0.08	-0.05	0.04	0.31	0.07	0.20	0.05
professionals_t_1	0.02	0.07					0.04	0.09	0.08	0.07
h_week_t_1	0.01	0.00					0.004	0.002	0.006	0.002
age_t_1	0.00	0.01	-0.03	0.02	0.06	0.01	0.008	0.01	-0.04	0.02
age2_t_1	0.00	0.00	0.00	0.00	0.00	0.00	-0.00002	0.00015	0.0003	0.0002
no_qualif	1.17	0.15	-0.07	0.32	-0.43	0.16	0.92	0.28	0.90	0.16
other_qualif	0.40	0.16	-0.02	0.33	-0.19	0.17	0.59	0.26	0.43	0.15
o_level	0.23	0.15	-0.04	0.33	-0.11	0.16	0.54	0.24	0.30	0.15
other_high_deg	-0.25	0.15	-0.20	0.33	0.34	0.16	0.19	0.27	0.03	0.18
Working in the last 5 years	0.14	0.03			0.00	0.00				
dist_kingston			0.003	0.0009						
dist_avg_altitude_t_1					-0.00001	0.000124				

All the regressions include year of survey fixed effects. Error term, reported in parentheses, is clustered at the individual level.