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Chutes and Ladders: Climate Variability and the Decision to Enter Sex Work in India

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Abstract:

There is widespread consensus that climate change will drive large-scale changes in poverty distributions, migration, and participation in risky informal labor markets, especially for poor households in developing countries which are both more likely to depend on the environment for their livelihood and less able to insulate against climate shocks. Within poor households, gender inequality means that women and children will bear a disproportional amount of welfare losses. I examine the impact of climate variability on migration and participation in risky informal labor markets for a particularly vulnerable population: female sex workers in India. Using a unique survey of 5,498 female sex workers from 122 origin districts, I use a proportional hazards model to test the impact of climate variability on the probability of entry into sex work in a given year. Contrary to the expected story of failed yields causing distress migration and entry into sex work, I find that favorable climate outcomes in the previous year predict entry. I present evidence that this finding is an investment effect, where women are saving up to migrate out of rural areas and enter sex work after a failed job search at the destination. I provide further evidence that contemporaneous climate variability has heterogeneous impacts by human capital level, suggesting that the most vulnerable, least educated women enter sex work due to distress migration while more educated women enter sex work after investment migration. These results suggest that policy to protect poor households from climate shocks by helping agriculture adapt may have unintended adverse consequences unless it is combined with urban formal sector job development. Because of the scarcity of data on sex workers, this paper is also among the first to examine sex work on the extensive margin.

Key words: Sex work, climate change, migration, human capital

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1. Introduction

In many of the countries predicted to be hardest hit by climate change, poor households are both more likely to depend on the environment for their livelihood and less able to insulate themselves from climate shocks (IPCC AR5). Within poor households, gender inequality means that women and children will bear a disproportionate amount of the welfare losses from adverse climate shocks. There is widespread consensus among environmental economists that climate change will drive large-scale changes in poverty distributions, migration, and participation in risky informal labor markets. To gain traction on these issues, this paper evaluates the impact of climate variability on the decision to enter sex work for women from rural districts of India.

Economists have begun to develop powerful tools for analyzing the economic impacts of climate variability and projections of climate change (Dell, Jones, and Olken 2014, Schlenker and Lobell 2010). In recent years, a literature on the human impacts of climate change has also grown rapidly, demonstrating links between climate shocks and cognitive and physical development (Anttila-Hughes and Dreesen 2015, Anttila-Hughes and Hsiang 2013, Tiwari, Jacoby, and Skoufias 2013, Maccini and Yang 2009) and between climate shocks and migration (Maystadt and Mueller 2012, Mueller, Gray, and Kosec 2014, Kleemans 2014). This paper contributes more evidence that climate variables can impact migration through both distress and investment channels.

Next, this paper contributes to an understanding of how climate change may impact participation in risky informal labor markets, such as migrant agricultural labor, harmful industrial work, and black and gray market labor. Sex work is a particularly under-studied informal labor market, both because of initial reluctance to characterize it as a market where sex workers are economic decision-makers and because of the difficulty of obtaining data on an activity that is frequently underground, illegal, and transient.

Finally, a growing economics literature on sex work has been motivated by the HIV epidemic. Researchers have focused on incentives for risk-taking along the intensive margin in order to identify causes of risky paid sex. Compensating differentials arising from client preference for non-condom use incentivize risky behavior (Gertler, Shah and Bertozzi 2005, Rao et al 2003). Female sex workers (FSWs) strategically capture these compensating differentials after income and health shocks in order to smooth consumption (Robinson and Yeh 2011, Dupas and Robinson 2010). However, little is known about the factors that influence decisions about entry in the first place. This research is among the first to examine decisions about sex work along the extensive margin.

In India, the location of this study, agriculture comprises 20 percent of GDP and employs 47 percent of the population (World Bank 2012). The majority of agricultural workers are poor, often farming plots of 5 acres and less without mechanization or access to credit markets and nonagricultural livelihoods near their homes. Income depends heavily on the precipitation and temperature outcomes that largely determine yields. Several studies have shown that climate change is already adversely affecting yields in India (Guiteras 2009, Gupta, Sen, and Srinivasan 2012, Jayaraman and Murari 2014).

This paper investigates the distributional impacts of climate variability by showing that climate variables predict the year of entry into sex work for female sex workers from agricultural regions of India. In India, sex work is highly stigmatized and, although transactional sex is legal, many key related activities are not.[1] Entry is usually a permanent decision: it is generally not possible to shed the label and for women in brothels, it is difficult to become financially independent again (Bhattacharya 2004, Sahni and Shankar 2013). Entry into sex work is thus a last resort rather than one occupational option among many[2], and a powerful descriptor of the experience of poverty.

In this paper, I combine a survey of 5,498 female sex workers (FSWs) with ERA-Interim precipitation and temperature data. Collected by the Avahan initiative to reduce HIV/AIDS transmission in India, the FSW survey is limited to the sex workers with the highest risk of spreading infection: those working in 22 districts of the four states with the highest disease rates who have migrated at least twice in the past two years. For this reason, the sample is not representative of Indian female sex workers in general and this paper does not claim external validity. However, the results are interesting in their own right and illuminate key areas for future research.

Because the sample includes only women who have entered sex work, I use a Cox proportional hazard model to evaluate the impact of climate outcomes on the probability of entry into sex work in a given year, conditional on eventual entry. I restrict my sample to the 1,879 women who come from rural districts. Following the growing climate economics literature (Dell, Jones, and Olken 2014), I use random year-to-year fluctuations in climate variables to proxy for changes in agricultural income.

Surprisingly, I find that favorable climate outcomes last year predict entry into sex work this year. Furthermore, women with different levels of human capital respond differently to contemporaneous climate outcomes. Illiterate women are more likely to enter sex work after an adverse contemporaneous climate outcome, while educated women are more likely to enter after a positive contemporaneous

[1] Transactional sex is not clearly treated by Indian Penal Code. It is addressed mainly by the Immoral Traffic (Prevention) Act (PITA), an amendment of the Immoral Traffic (Suppression) Act passed in 1956. Under PITA, sex work is legal but related

- Sex workers: illegal to solicit or engage in sex work near a public place, punishable by imprisonment with a fine
- Clients: illegal to engage in paid sex near a public place, punishable by imprisonment
- Pimps: illegal to pimp, punishable by imprisonment with a fine
- Live-in boyfriends of sex workers: illegal to live off a sex worker's earnings, punishable by imprisonment with a fine
- Brothels: illegal to own or manage a brothel, punishable by imprisonment with a fine
- Procuring and trafficking: illegal, punishable by 3-7 years' imprisonment with a fine

The government is obligated to provide rescue and rehabilitation to any sex worker who requests it. There is currently strong political debate over truly legalizing prostitution in order to better secure the health and safety of sex workers.

[2] For some castes, sex work is the traditional occupation. In this data, 1.8% of the women sampled cite "traditional family activity" as their reason for entry. These women are retained in the analysis because I am examining the impact of climate outcomes on the timing of entry conditional upon eventual entry, rather than the decision to enter.

outcome. These differential results are stronger for women who were in debt at the time of entry. Another 100 Growing Degree Days, a standard nonlinear measure of temperature, makes an FSW with some education and debt at time of entry more than twice as likely to enter sex work that year compared to her baseline hazard, significant at the 1 percent level. Conversely, another 100 Growing Degree Days makes an illiterate FSW with entry debt 61.5 percent *less* likely to enter sex work that year, significant at the ten percent level. In other words, Growing Degree Days accelerate entry for educated FSWs but delay entry for illiterate FSWs.

I argue that these results provide evidence that the mechanism through which some women have entered sex work may be investment migration, followed by a failed job search at the destination. Furthermore, climate variables have opposite impacts on illiterate and educated women. Illiterate women seem to be vulnerable to adverse climate outcomes, with a negative contemporaneous climate outcome predicting entry into sex work. Educated women, conversely, are more likely to enter sex work after a positive contemporaneous climate outcome, suggesting a pure migration story.

These results have important policy implications for forestalling climate-driven entry into risky informal labor markets, such as sex work, sweatshops, mining, and others; for anticipating and reducing climate-driven migration; and for reducing the transmission of STIs via sex work. As climate change drives increasing climate variability, the consequences will be the most acute for poor people in developing countries. This paper suggests that policy interventions to maintain yields by helping agriculture adapt will be insufficient to prevent rural to urban migration and entry into risky informal labor markets. Instead, promoting employment in rural areas to reduce migration in the first place and facilitating urban employment may be more effective in preventing entry into sex work.

2. Background

2.1 Climate change, welfare, and migration

Climate change is already adversely affecting agriculture in India. Guiteras (2009) estimates the impact of predicted future climate variability on Indian agriculture. Using a panel of over 200 districts from 1960-1999, he regresses yearly district-level yields on yearly climate measures and district fixed effects. In the medium term (2010-2039), climate change is predicted to reduce yields by 4.5-9 percent. In the long run (2070-2099), yields could fall by 25 percent or more. Gupta, Sen, and Srinivasan (2012) also predict significant damage to rice and millet yields in India using crop-specific production functions. However, Indian agriculture is still so low-tech that investment in agricultural technologies and mechanization could more than make up for the negative impacts of climate change (Guiteras 2009, Jayaraman and Murari 2014). Such large-scale investment is more plausible in the long run than the short run scenario. In the short run, the reduction in yields caused by climate change will probably intensify poverty (Jayaraman and Murari 2014).

While few studies have considered the impact of climate shocks on well-being in India, research in other countries provides insight. Kleemans (2014) estimates that a 5 percent increase in the standard deviation of climate shocks in Indonesia reduces consumption by 3.19 percent on average and 6.73 percent—more than twice as much—for the poorest half of the population. Positive monsoon rain shocks improve anthropometric measures of child health in rural Nepal through a positive income effect (Tiwari, Jacoby, and Skoufias 2013). Maccini and Yang (2009) show that early-life rainfall shocks can have long-term impacts. They find that positive early-life rainfall shocks in Indonesia improve later life health, education, and earnings outcomes for women but not men, revealing intrahousehold distributional inequality. Given the importance of climate outcomes in determining welfare, climate change is likely to disproportionately impact the poor in general and poor women and children in particular.

Finally, increasing climate variability will likely drive an increase in migration (Maystadt and Mueller 2012). Mueller, Gray, and Kosec (2014) find that heat stress drives long-term migration of Pakistani men, largely due to its negative impact on both farm and non-farm income. Using a large data set on migration in Indonesia, Kleemans (2014) identifies the impact of climate on distress versus investment migration.

2.2 Sex Work and Consumption Smoothing

A wide literature examines tradeoffs between short-term consumption smoothing and long-term well-being (Gertler and Gruber 2002, Jacoby and Skoufias 1997, Rosenzweig and Wolpin 1993, Paxson 1992). Households close to subsistence may sacrifice productive assets in order to meet immediate basic needs. Motivated by the HIV/AIDS epidemic, a growing literature on commercial sex builds upon theories of income and consumption smoothing to understand risk-taking within sex work.

The increasing riskiness of unprotected sex has created large compensating differentials for unprotected sex when the client prefers not to use a condom (Rao et al 2003, Gertler et al 2005, de la Torre et al 2010, Robinson and Yeh 2011, Arunachalam and Shah 2013). These compensating differentials are economically significant for sex workers, estimated at 9.3-46 percent depending on location, local disease risk, bargaining power, and other factors.

In the absence of adequate credit markets, sex workers strategically capture this compensating differential in order to maintain consumption after a shock. Robinson and Yeh (2011) find that sex workers in western Kenya "maintain consumption in large part by increasing their supply of unprotected sex and accepting significant health costs." On the day that a family member falls ill, women are 21.2 percent more likely to have anal sex and 19.1 percent more likely to have unprotected sex. The poorest women adjust their supply of high risk, high pay sex the most. Similarly, Dupas and Robinson (2010a) find that the income shocks during the 2008-9 post-election violence in Kenya caused sex workers to supply more and riskier sex in order to smooth incomes.

In addition, stable sex worker-client relationships sometimes provide a direct source of credit in the absence of formal credit markets. LoPiccalo, Robinson and Yeh (2012) find that a desire for insurance is one of the primary reasons that many of the sex workers in Busia, Kenya participate in sex work. Gifts from regular clients are a primary source of insurance during negative income shocks. In another study of Kenya, sociologists Luke, Mberu, and Zulu (2011) find that gift-giving and financial support form part of the cultural norm about dating. A desire for insurance also motivates decisions about unprotected sex for women with their boyfriends.

In effect, empirical work confirms that sex workers are trading off short-term consumption risk for long-term health risk. The use of higher-risk sex acts as a strategy for income smoothing suggests that improving access to formal credit markets may be a useful strategy for preventing STI transmission.

However, research so far examines responses along the intensive rather than extensive margin. Little is known about the decision to enter sex work in the first place. Qualitative research on the market for sex in India finds that the social stigmatization and illegality of solicitation are strong deterrents to entry, so that despite the fact that sex workers earn up to five times the income of their peers in other employments (Sahni and Shankar 2013), it is a last resort rather than one option among many. Eighty-nine percent of the women in this sample report entering into sex work due to force, negative circumstances in life, or economic conditions. Furthermore, entry into sex work is a permanent decision; it is extremely rare to exit sex work (Bhattacharya 2004).

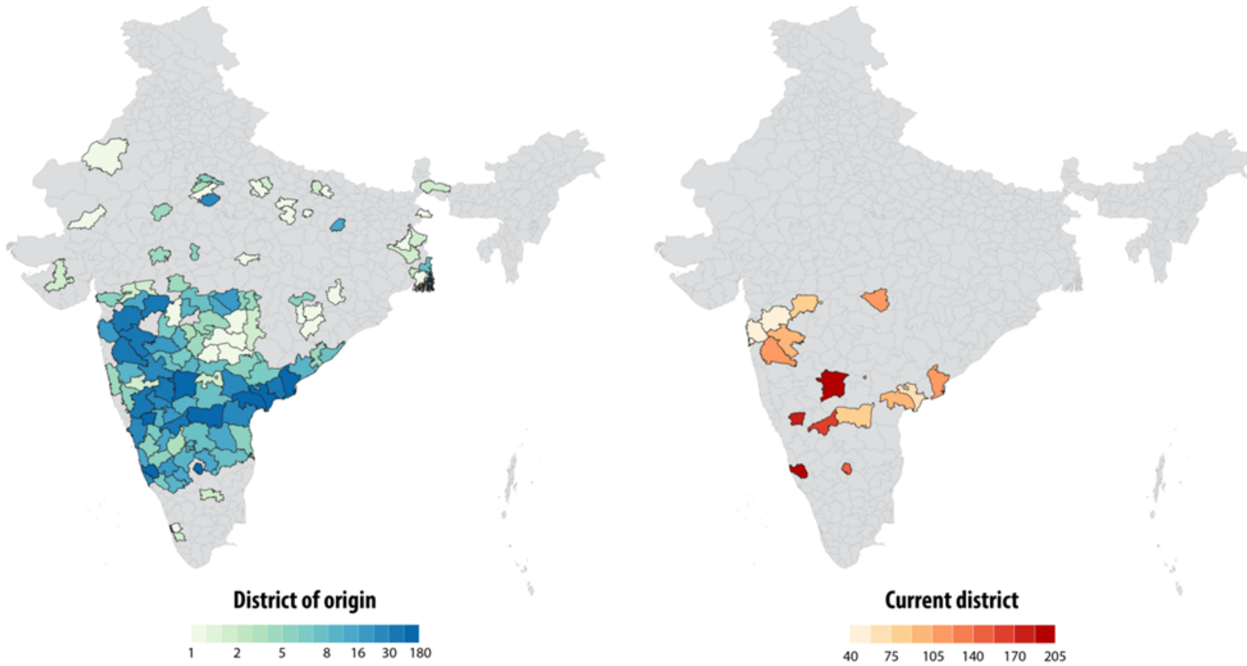
This paper is one of the first to describe the decision to enter sex work. As such, it has important implications for understanding STI epidemiology, as well as the distributional impacts of climate change.

3. Data

3.1 Female Sex Workers

In 2007-8, the Population Council conducted a cross-sectional survey of 5,498 female sex workers (FSWs) in 22 districts of four states as part of the Avahan project to combat HIV/AIDS transmission in India. FSWs were contacted through a two-step sampling procedure. First, both brothel and non-brothel solicitation sites were mapped and divided into spatial clusters containing approximately 500 FSWs each. Three clusters from each district were randomly selected. Enumerators systematically contacted FSWs in both brothels and open solicitation sites and surveyed FSWs who were over 18 years old and had moved to at least two places in the past two years of sex work, including at least one move across districts. The survey included both a quantitative structured questionnaire and a qualitative in-depth interview.

Figure 1. Female Sex Workers' Districts of Origin and Current Districts



This sampling strategy introduces unavoidable bias into this analysis. First, the data are not nationally representative: they include only FSWs who were working in those 22 districts of Andhra Pradesh, Karnataka, Maharashtra, and Tamil Nadu in the survey year. Second, the sampling strategy intentionally excludes any FSWs who had not moved in the past two years. FSWs who have moved recently are likely to be systematically different from those who have not. Finally, the survey is more likely to include the most visible FSWs. Sampling by mapping solicitation sites relies on being able to observe solicitation. FSWs who arrange client meetings by cell phone, work from their homes, or only engage in sex work occasionally are likely to be underrepresented or omitted entirely.

In addition, several key groups of sex workers are excluded. Male and transgender sex workers are excluded. Female sex workers younger than 18 are excluded, leaving out the important population of adolescents and children who have been sexually trafficked. However, because the survey asks about age at entry into sex work, it does include 118 adult women who began sex work before the age of 18.

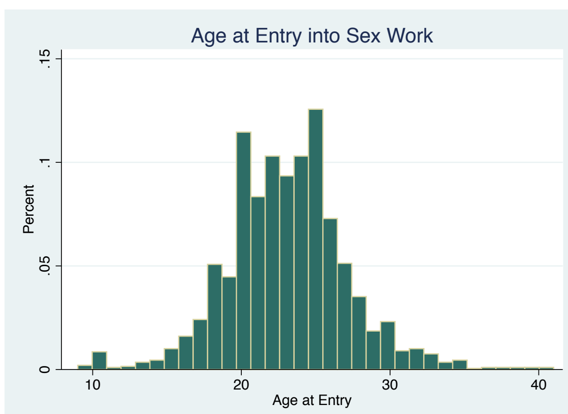
I further restrict the sample to the 1,879 women who report a rural district of origin, as defined by eligibility for the Government of India's Total Sanitation Campaign[3] (see Figure 1), and for whose origin district and lifetime I have climate data. In total, these women come from 119 districts in 14 origin states.

[3] A nationwide campaign to eliminate open defecation by 2017 through a combination of constructing sanitation infrastructure and changing social norms.

While the survey includes year of entry into sex work, it does not include the year of first emigration from the district of origin. For this reason, it is not possible to parse whether the entry and migration decisions are joint or consecutive. In other words, it is not possible to determine whether women are migrating in order to enter sex work, entering sex work in the home district and then migrating elsewhere, or migrating and then entering sex work. However, it is possible to argue that the latter is most likely. The social ramifications for entering sex work are so severe that women from small, rural villages typically move first (Bhattacharya 2004), and often conceal their occupation from their families and acquaintances back home, sometimes by also engaging in a more acceptable additional occupation (Sahni and Shankar 2013). In fact, 72 percent of the women surveyed report having a second occupation, although this second occupation is economically insignificant compared to their earnings from sex work. In this analysis, I treat year of entry into sex work as the year of emigration from the origin district.

The women sampled tend to be in their 20s; the oldest was 55 years old at the time of survey. Thirty six percent report having no education and 71 percent reached standard five or lower. Seventy two percent are Scheduled Tribe, Scheduled Caste, or Other Backward Castes. Seventy seven percent are Hindu, 15 percent Muslim, and six percent Christian, comparable to the general population.

Figure 2. The Distribution of Age at Entry into Sex Work



The median age at entry is 24; the youngest age at entry is 9 and the oldest is 41. On average, these women have had 1.45 abortions, one son, and one daughter. Physical safety is a problem. Nearly 3 in 10 women report experiencing violence in their place of work. More than half of the women sampled have had intercourse with clients who refused to use condoms, and 83 percent say it is difficult to negotiate the use of condoms after moving to a new place. Four in ten worry they are at moderate to high risk of contracting HIV. Additional descriptive statistics are included in Table 1.

3.2 Climate

I use climate data from the European Centre for Medium-range Weather Forecasting (ECMWF) ERA-Interim (ERA-I) reanalysis dataset. This dataset provides daily measures of an extensive set of meteorological variables, of which I use temperature and precipitation.

Reanalysis data combine observations from diverse sources, including weather stations and satellites, and use them as inputs to an atmospheric model that interpolates the data both spatially and temporally. This results in a consistent gridded dataset at a 0.75x0.75 degree native resolution, which ECMWF then further downscales to 0.25x0.25 degree resolution. This results in 129 x 121 pixels for each day of the year from 1979 to 2012. I take district area-weighted averages of these 182 million observations to get temperature and precipitation data for more than 550 districts in India.

The ERA-I is one of the most studied and validated of the modern reanalysis datasets available (Lindsay et al 2014). Reanalysis offers advantages over data from weather stations, whose placement is endogenous and therefore might result in biased coverage. Furthermore, many weather stations offer inconsistent time-series and observation periods. The combination of observations from diverse sources as well as atmospheric modeling to interpolate between them makes reanalysis data more reliable than station data (Auffhammer et al 2013). Summary statistics for the ERA-I data are presented in Table 2.

3.2.1 Degree days

My identification strategy relies on the idea that agricultural shocks in districts of origin will impact the likelihood of entry into sex work in that year. To more accurately capture the impact of temperature on crop yields, I convert the daily temperature data obtained from ERA-I into degree days. Degree days are a transformation of time spent at a certain temperature. Plant physiology responds positively to temperatures within a certain range, but is damaged by temperatures above a certain threshold. Average temperatures do not capture this nonlinearity in plants' response to temperature. A well-identified literature demonstrates the accuracy of this approach to modeling crop responses to climate (Schlenker and Roberts 2009, Schlenker and Lobell 2012).

The literature shows that these thresholds differ across crops. However, since it is not possible to observe the agricultural production of the women in our dataset, I choose general thresholds that could apply to a large number of crops while noting that this will introduce some error in exact exposures.

I define "Growing Degree Days" (the beneficial temperature exposure) as days spent at a specific number of degrees between 8°C and 32°C. That is, one day at 18°C would be 10 degree days. I define "Killing Degree Days" (the damaging exposure) as days spent above 32°C. That is, one day at 35°C would contribute 22 Growing Degree Days and 3 Killing Degree Days. To perform this transformation, I obtain sub-daily data on maximum and minimum temperatures and use these to fit a curve of hourly temperature to the data following Schlenker and Roberts (2009). Degree-hours within each of the ranges above are calculated and transformed into degree-days. I sum these degree days to create totals for the main kharif growing season and the full year.

3.3 Crop Yields

Data on crop yields are reported by the Directorate of Economics & Statistics, Ministry of Agriculture, Government of India by district and crop for the period 1998-2013 in the states of Andhra Pradesh, Karnataka, Maharashtra, and Tamil Nadu. I construct three different indices of crops, following Guiteras (2009) to construct a strict index of subsistence crops, a second broader index of subsistence crops, and the Government of India's definitions to construct an index of cash crops. Yields are measured in volume of output per hectare. Summary statistics are presented in Table 3.

Definition of Crop Types

Crop Type	*Crops*
Subsistence crop	Rice, maize, corn, jowar, bajra, wheat
Major crop	Rice, maize, corn, jowar, bajra, wheat, arhar, gram, ragi
Cash crop	Arecanut, banana, black pepper, cardamom, castor seed, coconut, coriander, cotton, dry chillies, dry ginger, garlic, groundnut, guar seed, linseed, mesta, niger seed, rapeseed mustard, safflower, sesamum, soyabean, sugarcane, sunflower, sweet potato, tapioca, tobacco, turmeric

4. Estimated Model

My identification strategy exploits plausibly random yearly variations in temperature and precipitation to determine their causal impact on the year of entry into sex work, conditional on eventual entry and fixed effects. Because the sample is comprised only of women who did enter sex work, there is no comparison group of women who did not. Consequently, it is not possible to estimate the impact of climate on *whether* a woman enters sex work. Instead, I estimate the impact of climate on *when* she enters, conditional on eventual entry. I use a Cox proportional hazards model to estimate how climate variables change the risk of entry in a given year, conditional on eventual entry into sex work. Climate variables can be thought of as accelerating or delaying inevitable entry into sex work. The counterfactual then becomes all the years in which the same individual did not enter sex work.

The Cox proportional hazards model is based on survival analysis models in medical research, which estimate the impact of treatments and exposures on survival time. This group of models is also frequently referred to as "duration analysis" because the dependent variable is defined as time to an event of interest, such as death, recovery, or release from the hospital. The dependent variable is often called "failure" or "exit from the initial state." The treatment effect is estimated relative to an underlying hazard rate to capture the fact that failure may happen regardless of treatment, i.e., everyone dies eventually. The hazard function for event T occurring in the interval $[t, t+h)$, given survival up until time t, is defined as

$$\lambda(t) = \lim_{h \to 0} \frac{P(t \leq T < t + h | T \geq t)}{h}$$

Assuming that the probability density function and conditional density function are differentiable, the probability of the event occurring in any interval can be computed using the hazard function. Following Wooldridge (2010), for points $t_1 < t_2$, I can write

$$P(t_1 < T \leq t_2 | T \geq t_1) = 1 - \exp\,[-\int_{t_1}^{t_2} \lambda(s) ds]$$

where $\lambda(s)$ is the hazard function. Some survival analysis models rely on assumptions about the distribution of T, imposing assumptions on the shape of the baseline hazard function. The simplest example is specifying that T is not duration-dependent, so that the probability of failure does not change over time. Then the hazard rate is constant and the cdf of T is exponential. Common specifications for the hazard function are log-logistic and exponential.

Here, there is no theoretical reason to impose a functional form on the hazard function[4]. To avoid force-fitting the data, I use a proportional hazards model to estimate the relative impact of an independent variable on exit from the initial state. The baseline hazards cancel out so that they never need to be specified, although there are post-estimation techniques for calculating the baseline hazard (see Figure 4). Accordingly, I examine the factors that affect the timing of entry into sex work given that every subject eventually "fails," or enters sex work.

I use a grouped duration approach to examine remaining in the initial state (not entering sex work) or exiting the initial state (entering sex work) as a binary outcome in each one-year interval. The binary dependent variable is equal to 1 in the year of entry. Again, because the Cox hazards model is proportional, no functional form is imposed on the underlying hazard model. However, because different age groups and origin districts are likely to have different baseline hazards, I use age group and origin district strata (see Figure 4). I set the time a woman becomes "at risk" at age 9 instead of at birth, since children younger than that are unlikely to enter sex work. Using this specification, the minimum "survival time" or "duration" is zero years and the maximum is 32 years, meaning that age of entry ranges from 9 years to 41 years old.

I estimate the following Cox proportional hazards model:

$$\lambda(t, X'(t)) = \kappa[\exp(\beta X'(t))]\lambda_0\,(t)$$

where the hazard λ of entry into sex work is a function of time t, time invariant individual characteristics,

[4] A Poisson regression could also be appropriate here, but its assumptions about distribution make it less accurate. Tests on Poisson results reveal over-dispersion even when using robust standard errors to correct for heteroskedasticity.

and exogenous time-varying covariates. This specification allows exogenous time-varying covariates to have a multiplicative impact on the baseline hazard in each time interval, meaning that climate variables multiply the baseline hazard rate to either increase or decrease the probability of entry in a given year. Past values of the covariates, including lagged climate variables, are included as covariates at time *t*.

In this paper, regression results are reported as relative hazard ratios. Hazard ratios should be interpreted as multiplying the baseline hazard, so that a hazard ratio less than one decreases the probability of entry in a given year and a hazard ratio greater than one increases the probability of entry. For an additional unit of the explanatory variable X_i, the hazard of entry this year changes by $e^{\beta_i} - 1$ percent. See Figure 4 for plots of baseline hazards by age group, origin district, caste, and religion.

5. Results

5.1 Crop Yields and Climate Variables

I regress crop yields on climate variables and fixed effects to verify the channel between climate variables and agricultural income. These results are in line with a large and well-identified agriculture and economics literature.

Indian agriculture spans two growing seasons, the main kharif growing season from June to November and the minor rabi growing season from November to February. Kharif yields are largely determined by monsoon precipitation in June to August. I test the correlation between kharif and annual climate variables on kharif and annual yields for three major crop types: a strictly defined set of subsistence crops, a wider set of "major" subsistence crops, and cash crops. These results are robust to using kharif, monsoon, or annual precipitation and to including an interaction between Degree Days and precipitation to capture the fact that precipitation diminishes the harmfulness of Killing Degree Days (KDD) and augments the benefit of Growing Degree Days (GDD).

I find that precipitation, KDD, and GDD predict more than 65 percent of the variation in crop yields, in line with other estimates that do not include soil quality or inputs like fertilizer, cultivation techniques, and labor. KDD are strongly negatively correlated with crop yields: another 100 kharif KDD is associated with a 14.9 percent decrease in kharif yields for every crop type, significant at the 1 percent level. GDD and precipitation are positively correlated with yields in every specification, though their impact is smaller and not significant in every specification. See Table 4 for results.

5.2 Crop Yields and Entry into Sex Work

I use district-level data on crop yields for the states of Andhra Pradesh, Karnataka, Maharashtra, and Tamil Nadu to explore the correlation between crop yields and year of entry into sex work. The crop yield data spans 1998-2013, so the sample shrinks to the 1,433 women whose home districts lie in these states and who entered sex work during these years.

I estimate the following model:

$$\lambda(t, Y_i(t)) = \kappa[\exp(\beta Y_i(t))]\lambda_0(t)$$

where $Y_i(t)$ represents district-level yields, and κ represents controls including time-invariant individual controls (marital status, religion, and caste), year fixed effects, and state-time fixed effects. As discussed above, I use origin district and age group strata and cluster errors at the district level because error is likely to be highly correlated across areas with shared soil types, climate outcomes, and other agricultural characteristics.

Table 5. Correlation between Crop Yields and Year of Entry†

	(1)	(2)	(1)	(2)	(1)	(2)
	Subsistence Crops		Major 10 Crops		Cash Crops	
VARIABLES	Kharif	Annual	Kharif	Annual	Kharif	Annual
Yield	0.942	1.034	0.899	1.018	1.062	0.894
	(0.0945)	(0.0738)	(0.116)	(0.0741)	(0.0410)	(0.187)
Lag yield	0.837	0.815	0.804	0.809	0.858*	0.646**
	(0.113)	(0.112)	(0.166)	(0.127)	(0.0719)	(0.137)
Lag 2 yield	0.781***	0.923	0.780**	0.918	1.014	0.837
	(0.0658)	(0.107)	(0.0954)	(0.113)	(0.0236)	(0.131)
N	1,249	1,247	1,237	1,247	1,244	1,144
Observations	4,693	4,632	4,695	4,632	4,673	4,321
Pseudo R-squared	0.0849	0.0828	0.0848	0.0827	0.0854	0.0883

Includes precipitation squared (to capture diminishing effects), state fixed effects, crop fixed effects, state-time linear and quadratic trends, and year fixed effects. Errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

† Includes districts in Andhra Pradesh, Karnataka, Maharashtra, and Tamil Nadu only.

The hazard ratio for contemporaneous yield is not significant, nor is the effect consistent, across crop types and kharif versus annual specifications. The hazard ratios on the one and two year lagged yields are mainly less than one and occasionally significant. Overall, the results are neither strong nor clear.

For several reasons, this is to be expected. First, climate may impact the timing of entry into sex work through channels other than agricultural incomes. Second, there are endogeneity concerns between crop yields and timing of entry. An omitted variable could be jointly determining both, from the death of a family member to intrahousehold bargaining dynamics. It is also possible that higher yields are correlated with greater wealth, since fertilizer and mechanization both improve yields but are unaffordable for the poorest farmers, and therefore a later entry into sex work. In conclusion, it is neither surprising nor concerning that crop yields do not directly predict year of entry even though I expect that climate variables impact entry through an agricultural channel.

5.3 Main Specification: Climate Variables and Entry into Sex Work

Exploiting the randomness of yearly climate fluctuations, I test the causal impact of climate variables on entry into sex work, controlling for year fixed effects, state-time trends, individual controls, and district and age group strata. To capture the diminishing impact of precipitation on yields, I include a quadratic precipitation term. Following the agricultural literature, I also include an interaction term between precipitation and degree days to capture the positive impact of rainfall on the benefits of GDD and the ameliorating impact of rainfall on the harmfulness of KDD (Table 7 in the Appendix shows that results are similar for a specification without the interaction between degree days and precipitation).

Contrary to the hypothesis that adverse climate shocks drive entry into sex work by reducing agricultural incomes, I find that favorable contemporaneous annual climate outcomes make entry this year more likely. The hazard ratios for lag annual climate variables, though not statistically significant, also indicate that favorable outcomes last year make entry more likely. This lag effect is similar in magnitude and statistically significant for kharif climate variables. However, the hazard ratios for contemporaneous kharif climate outcomes point in the opposite direction, with adverse climate outcomes this year predicting entry—although these estimates are not statistically significant, and the true effect may be that favorable contemporaneous kharif outcomes also make entry more likely.

Table 6. Effect of Climate Variables on Year of Entry

	Kharif			Annual		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	No lags	1 lag	2 lags, 1 lead	No lags	1 lag	2 lags, 1 lead
GDD (100s)	0.939	0.968	0.941	1.204**	1.213**	1.238***
	(0.101)	(0.108)	(0.122)	(0.0957)	(0.0952)	(0.102)
KDD (100s)	1.448	1.048	1.116	0.617	0.585	0.475
	(0.644)	(0.598)	(0.680)	(0.272)	(0.266)	(0.224)
Precipitation (total mm)	1.002	1.002	1.001	1.002	1.002	1.002
	(0.00263)	(0.00282)	(0.00349)	(0.00298)	(0.00307)	(0.00305)
Lag GDD (100s)		1.002**	1.002**		1.001	1.001
		(0.000852)	(0.000983)		(0.00069)	(0.00076)
Lag KDD (100s)		0.993**	0.993*		0.999	0.998
		(0.00362)	(0.00383)		(0.00177)	(0.00202)
Lag Precipitation (total mm)		1.001	1.001		1.000	1.000
		(0.000409)	(0.000487)		(0.00032)	(0.00032)
Observations	24,127	24,052	23,954	24,127	24,052	23,954
N subjects	1701	1701	1701	1701	1701	1701
Pseudo R-squared	0.131	0.132	0.131	0.131	0.132	0.131

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.4 Heterogeneous Impacts on Subgroups of Female Sex Workers

I run the same specifications for subgroups of FSWs by education level. The results for the impact of kharif climate variables are inconclusive, although there is a large jump in the magnitude and direction of the impact of GDD and KDD for women with low levels of education (up to primary school) compared to women with high levels of education (secondary school and above). More GDD make entry for low-type women less likely and entry for high-type women more likely.

However, every subgroup still displays the positive lag effect: positive climate outcomes last year predict entry this year at a similar magnitude for women at every human capital level.

Table 8. Heterogeneous Impacts of Kharif Climate Impacts on Year of Entry

VARIABLES	(1) All Education Levels	(2) Illiterate	(3) Primary School	(4) Secondary School	(5) Secondary and Above
GDD (100s)	0.941	0.808	0.936	1.228	1.218
	(0.122)	(0.188)	(0.215)	(0.266)	(0.254)
KDD (100s)	1.116	0.464	0.00749**	5.372	4.783
	(0.680)	(0.766)	(0.0166)	(7.060)	(5.862)
Precipitation (total mm)	1.001	1.000	1.001	1.005	1.004
	(0.00349)	(0.00719)	(0.0102)	(0.00446)	(0.00466)
Lag GDD (100s)	1.002**	1.002	1.005	1.000	1.001
	(0.000983)	(0.00186)	(0.00315)	(0.00171)	(0.00144)
Lag KDD (100s)	0.993*	0.993	0.987	0.994	0.990*
	(0.00383)	(0.00624)	(0.00918)	(0.00579)	(0.00594)
Lag Precipitation (total mm)	1.001	1.000	1.001	1.001	1.001**
	(0.000487)	(0.000949)	(0.00151)	(0.000728)	(0.000589)
Observations	23,954	8,383	5,596	8,528	9,975
N subjects	1701	590	384	619	727
Pseudo R-squared	0.131	0.162	0.187	0.183	0.173

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, two lags and one lead, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results for FSWs with primary school education and debt at time of entry are not reported due to a missing likelihood.

Next, I select only the women who were in debt at the time of entry into sex work before dividing them by human capital level. Now a strong and opposite effect emerges for illiterate versus educated women. Another 100 GDD makes an illiterate woman 61.5 percent less likely to enter sex work, while a woman with some level of education becomes more than twice as likely to enter. The hazard ratios for KDD and precipitation are not always statistically significant, but their magnitudes are consistent with the observation that the impact of contemporaneous climate variables is opposite for illiterate versus educated women. Furthermore, the lag effect remains consistent across every subgroup. (Tables 10-13 in the Appendix present the full set of results for subgroups with and without entry debt using both kharif and annual variables.)

Table 9. Heterogeneous Impacts of Kharif Climate Impacts on Year of Entry, with Entry Debt

VARIABLES	(1) All Education Levels	(2) Illiterate	(3) Some Education	(4) Secondary and Above
GDD (100s)	1.054	0.385*	2.190***	2.464**
	(0.194)	(0.189)	(0.659)	(0.931)
KDD (100s)	0.0243***	0.276	0.0134**	0.00590*
	(0.0328)	(0.609)	(0.0256)	(0.0170)
Precipitation	1.010**	1.004	1.014	1.012
(total mm)	(0.00476)	(0.0102)	(0.00920)	(0.0102)
Lag GDD (100s)	1.004*	1.004	1.003	1.003
	(0.00212)	(0.00301)	(0.00261)	(0.00230)
Lag KDD (100s)	0.981**	0.974***	0.981**	0.968**
	(0.00792)	(0.00948)	(0.00879)	(0.0126)
Lag Precipitation	1.002**	1.001	1.003***	1.003***
(total mm)	(0.000930)	(0.00112)	(0.00110)	(0.00102)
Observations	9,320	3,701	5,619	4,051
N subjects	665	253	412	301
Pseudo R-squared	0.180	0.258	0.204	0.265

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, two lags and one lead, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results for FSWs with primary school education and debt at time of entry are not reported due to a missing likelihood.

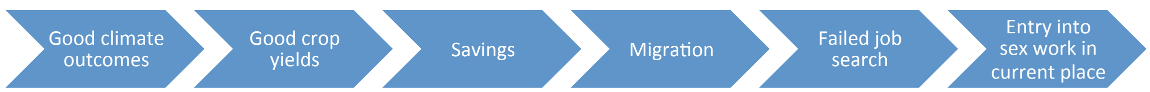
6. Discussion

This paper presents two surprising findings. First, for this sample of FSWs, climate migration and entry into sex work is at least partially an investment story. Second, climate variables may have heterogeneous impacts depending on human capital level. These results are clear, but the mechanisms through which they operate are not. In this section, I suggest causal chains for each result and provide supporting evidence. However, additional data are needed to credibly establish these mechanisms.

6.1 Climate-Driven Investment Migration as a Pathway into Sex Work

For every specification run on every subsample, favorable climate outcomes last year predict entry this year: the hazard ratios for the beneficial lag climate variables, GDD and precipitation, are greater than one and the hazard ratio for the harmful lag climate variable, KDD, is less than one. These results suggest that climate variables impact year of entry through their impact on migration, consistent with a standard two-sector model with urban job search. Good climate outcomes increase crop yields (see Table 4), enabling households in low-wage rural areas to save up to migrate to urban areas, where they hope to secure a more lucrative job. Because formal sector urban jobs are scarce, many migrants end up in high-risk informal labor.

Figure 3. Hypothetical Causal Chain



Although the data do not allow me to determine whether the migration and entry decisions are made jointly or sequentially, I have argued that a sequential decision is most likely. The social ramifications for entering sex work are so severe that women from small, rural villages typically move first (Bhattacharya 2004), and often conceal their occupation from their families and acquaintances back home, sometimes by also engaging in a more acceptable additional occupation (Sahni and Shankar 2013). In fact, 72 percent of the FSWs surveyed report having a second occupation, although income from the second occupation is trivial compared to income from sex work. Monthly earnings from non-sex work occupations average Rs 302, compared to Rs 17,885 for sex work. This earnings differential suggests that the second occupation is used as a social rather than economic tool.

Additional evidence supports the interpretation of this lag result as an investment effect. A wide literature establishes that people from rural agricultural areas save up to migrate to cities in order to secure better employment and, often, to send remittances home. Nearly half of the women in this sample send remittances. The average monthly income from both sex work and non-sex work for FSWs who remit is Rs 20,304. On average, remitters send 39 percent of their income home—about Rs 7,919. According to the 2009-2010 National Sample Survey, average monthly per capita consumer expenditure in rural areas is Rs 1,054. The average remittance is seven times average monthly income, representing a tremendous contribution to their families' well-being. The imperative to remit supports the story that women migrate in order to find better jobs; when they fail to find those jobs, they enter sex work in the current place instead of returning home.

I can also get some traction by comparing the number of times an FSW has migrated with her entry year. The sample is restricted only to FSWs who have moved at least twice in the two years preceding the survey. If these women entered sex work in their origin districts, then their entry year should also fall within two years of the survey. This is the case for only 24 of the 49 FSWs in the sample who have moved only twice.

Still, this causal chain is speculative. To rigorously identify the mechanism, better data are needed on the timing of migration.

6.2 Heterogeneous Impact of Climate Variables by Human Capital Level

Dividing the sample by human capital level suggests that climate variables may have different impacts for low-educated versus highly-educated women. Although the results are not statistically significant, the point estimates of the hazard ratios indicate that illiterate women are more likely to enter after adverse contemporaneous climate outcomes, while educated women are more likely to enter after favorable contemporaneous climate outcomes.

These results become statistically significant and increase in magnitude when I examine only the FSWs who were in debt when they entered sex work. For illiterate, indebted women, another 100 GDD makes entry this year 61.5 percent less likely relative to their baseline hazard, significant at the 10 percent level. The hazard ratios for KDD and precipitation are not statistically different from one. For secondary and above-educated, indebted FSWs, another 100 GDD makes entry this year more than twice as likely, significant at the 1 percent level, and another 100 KDD makes entry this year about half as likely, significant at the 5 percent level. For each of these regressions, the pseudo R-squared is greater than 0.20. While there are many contributing factors to entering sex work, climate variability is a meaningful component.

What causes the heterogeneity in the impact of climate variables for FSWs with different levels of human capital? And why does being in debt at the time of entry strengthen the different results for these subgroups of women?

In her 2014 study of Indonesia, Kleemans finds that migration falls into two categories: cheaper, shorter distance distress migration caused by an adverse shock, and more expensive, longer-distance, and ultimately more lucrative investment migration enabled by a series of positive shocks. I suggest that the heterogeneous results by human capital level tell a similar story.

I hypothesize that the most vulnerable women are being pushed into sex work by adverse climate outcomes, following a typical distress entry and distress migration story. Negative climate shocks cause the crops to fail; to survive, women leave their home district and enter sex work. Adding the entry debt stipulation may strengthen the results because sex work is a last-ditch option (Bhattacharya 2004). These women likely borrowed before deciding to enter sex work.

Conversely, women with some human capital seem to follow an investment migration story. They save up after good climate outcomes and then migrate to cities and enter sex work. Their results get stronger with entry debt because they may be taking out a loan or borrowing from family to facilitate investment migration, which tends to be longer-distance and more expensive than distress migration (Kleemans 2014).

In order to establish this mechanism, data are needed on both the timing and pattern of migration to confirm that illiterate and educated women follow patterns of distress versus investment migration.

7. Conclusion

Contrary to the expected story of adverse climate outcomes causing distress entry into sex work, this paper provides evidence for a more complex interaction between climate, migration, and harmful informal labor markets—in this case, sex work. A better understanding of this intersection is urgent given projections of significant damage to Indian agriculture due to climate change.

These results suggest that policy interventions to help agriculture adapt to climate change will be insufficient to prevent rural to urban migration and entry into risky informal labor markets like sex work. In fact, increasing yields may actually increase migration and entry into such jobs. Instead, facilitating urban formal sector employment may be more effective in preventing entry into risky informal jobs. Moreover, diversifying rural employment opportunities and increasing educational attainment may reduce vulnerability to climate shocks.

As some of the first research to gain traction on the extensive margin of the market for sex, these results also suggest that policy seeking to reduce the transmission of HIV/AIDS and other STIs should focus on formal sector urban job development and making the job search process easier for recent migrants. Job training programs may be a necessary component of such a policy, given the low levels of education among sex workers; lack of education may have been a barrier to securing a desirable job for many of these women in the first place.

While this paper achieves causal identification of the impact of climate variability on entry into sex work for this sample of women, data limitations prevent a similar identification of its impact on migration. An outline for further research should seek detailed migration data to clearly identify 1) whether the decisions to migrate and to enter sex work, or another risky informal sector occupation, are made simultaneously or consecutively; 2) whether climate outcomes have heterogeneous impacts on the migration patterns of subsets of individuals defined by human capital level, wealth, or some other measure of vulnerability.

Table 1. Sex Worker Summary Statistics

	Mean	*Std. Dev.*	*Min*	*Max*	*N*
Age at survey (yrs)	28.15	4.69	18	55	1879
Age at first sex (yrs)	16.99	2.801	9	29	1879
Age at first marriage (yrs)	16.64	3.23	9	29	332
Age at entry (yrs)	23.15	4.10	9	41	1879
Education (yrs)	3.73	3.40	0	25	1879
	Freq.	*Percent*	*Cum.*		
Illiterate	654	34.77	34.77		
Primary school	402	21.37	56.14		
Secondary school	700	37.21	93.35		
High school and above	125	6.65	100.00		
In debt at entry	719	38.22	38.22		
In debt at survey	804	42.79	42.79		
Sends remittances	844	47.63	47.63		
Religion					
Hindu	1474	78.45	78.45		
Muslim	255	13.57	92.02		
Christian	117	6.23	98.24		
Other	33	1.76	100.00		
Caste					
Scheduled Caste	512	29.96	29.96		
Scheduled Tribe	195	11.41	41.37		
Other Backward Castes	551	32.24	73.61		
Other	451	26.39	100.00		
Sex work	*Mean*	*Std. Dev.*	*Min*	*Max*	*N*
Days per week	5.24	1.34	1	7	1879
Clients per day	4.89	3.080	1	29	1879
Monthly income from sex work	17,885.3	19,982.7	960	260,000	1879
Monthly income from other sources	321.89	750.96	0	15,000	1879
Percent remitted	38.97	19.27	10	75	844
Amount in debt	12,421.68	82,112.51	0	2000000	803

Table 2. ERA-Interim Descriptive Statistics for FSW Origin Districts, 1979-2007

	Mean	*Std. Dev.*	*Min.*	*Max.*	*N*
Temperature, annual avg, C	25.73	1.27	10.12	28.73	3,025
Temperature, monsoon avg, C	26.06	2.30	16.11	36.45	3,025
Temperature, kharif avg., C	25.37	1.65	13.69	33.16	3,025
Precipitation, annual total mm	936.69	508.92	24.40	3279.65	3,025
Precipitation, monsoon total mm	526.93	338.32	13.83	1932.90	3,025
Precipitation, kharif total, mm	814.978	429.06	13.90	2597.66	3,025
Growing Degree Days (GDD), annual total	3,449.74	239.91	681.49	4,014.34	3,025
Growing Degree Days, monsoon total	1,641.28	191.43	747.09	2,190.41	3,025
Growing Degree Days, kharif total	3,156.62	281.24	110.83	4,025.72	3,025
Killing Degree Days (KDD), annual total	60.61	43.69	0.00	443.69	3,025
Killing Degree Days, monsoon total	18.01	25.45	0.00	426.29	3,025
Killing Degree Days, kharif total	20.51	27.82	0.00	578.70	3,025

Table 3. District- Level Crop Yields Summary Statistics, 1998-2013*

	Mean	*Std. Dev.*	*Min.*	*Max.*	*N*
Subsistence, annual, output/hectare	1.98	0.81	0.19	6.02	12615
Subsistence, kharif, output/hectare	1.68	0.55	0.32	3.90	12886
Major crop, annual, output/hectare	1.84	0.70	0.19	6.02	12615
Major crop, kharif, output/hectare	1.41	0.47	0.29	2.92	12888
Cash crop, annual, output/hectare	0.87	0.49	0.13	2.69	11974
Cash crop, kharif, output/hectare	1.95	2.42	0.12	20.16	12875

**For districts in Andhra Pradesh, Karnataka, Maharashtra, and Tamil Nadu only.*

Table 4. Effect of Climate Variables on Crop Yields†

	(1)	(2)	(1)	(2)	(1)	(2)
	Subsistence Crop		Major Crop		Cash Crop	
VARIABLES	Kharif	Annual	Kharif	Annual	Kharif	Annual
KDD (100s)	-0.149***	-0.0769**	-0.155***	-0.0820**	-0.171***	-0.150***
	(0.0508)	(0.0387)	(0.0473)	(0.0340)	(0.0561)	(0.0364)
GDD (100s)	0.0157	0.00906	0.0430***	0.0110	0.0292*	0.0151
	(0.0162)	(0.0100)	(0.0152)	(0.00952)	(0.0168)	(0.0127)
Precipitation (total mm)	0.000595	0.00276***	0.000967**	0.00229**	0.000569	0.000386
	(0.000583)	(0.000976)	(0.000483)	(0.000896)	(0.000473)	(0.000828)
Observations	4,270	2,499	6,233	3,039	6,913	2,202
R-squared	0.669	0.752	0.696	0.777	0.880	0.877

Includes precipitation squared (to capture diminishing effects), state fixed effects, crop fixed effects, state-time linear and quadratic trends, and year fixed effects. Errors are clustered at the district level and presented in parentheses. Results for log yields (not shown) are similar. *** p<0.01, ** p<0.05, * p<0.1

† Includes districts in Andhra Pradesh, Karnataka, Maharashtra, and Tamil Nadu only.

Table 7. Effect of Climate Variables on Year of Entry, without Degree Day-Precipitation Interaction

	Kharif			Annual		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	No lags	1 lag	2 lags, 1 lead	No lags	1 lag	2 lags, 1 lead
GDD (100s)	0.897	0.924	0.914	1.151***	1.169***	1.188***
	-0.109	-0.112	-0.117	-0.0521	-0.0541	-0.0565
KDD (100s)	0.84	0.744	0.745	0.776	0.738	0.682*
	-0.264	-0.266	-0.332	-0.167	-0.164	-0.158
Precipitation (total mm)	0.999	0.999	0.999	1.000	1.000	1.001
	-0.00091	-0.00094	-0.00108	-0.00058	-0.00057	-0.00056
Lag GDD (100s)		1.002***	1.002**		1.001	1.001
		-0.0008	-0.00096		-0.00069	-0.00076
Lag KDD (100s)		0.993**	0.993*		0.999	0.998
		-0.00342	-0.00368		-0.00174	-0.00193
Lag Precipitation (total mm)		1.001*	1.001		1	1
		-0.00039	-0.0005		-0.0003	-0.00031
Observations	24,127	24,052	23,954	24,127	24,052	23,954
N subjects	1701	1701	1701	1701	1701	1701
Pseudo R-squared	0.131	0.131	0.131	0.131	0.132	0.131

Includes precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Effect of Climate Variables on Year of Entry, by Education Level

	Kharif				
VARIABLES	(1) All Education Levels	(2) Illiterate	(3) Primary School	(4) Secondary School	(5) Secondary and Above
GDD (100s)	0.941	0.808	0.936	1.228	1.218
	(0.122)	(0.188)	(0.215)	(0.266)	(0.254)
KDD (100s)	1.116	0.464	0.00749**	5.372	4.783
	(0.680)	(0.766)	(0.0166)	(7.060)	(5.862)
Precipitation (total mm)	1.001	1.000	1.001	1.005	1.004
	(0.00349)	(0.00719)	(0.0102)	(0.00446)	(0.00466)
Lag GDD (100s)	1.002**	1.002	1.005	1.000	1.001
	(0.000983)	(0.00186)	(0.00315)	(0.00171)	(0.00144)
Lag KDD (100s)	0.993*	0.993	0.987	0.994	0.990*
	(0.00383)	(0.00624)	(0.00918)	(0.00579)	(0.00594)
Lag Precipitation (total mm)	1.001 (0.000487)	1.000 (0.000949)	1.001 (0.00151)	1.001 (0.000728)	1.001** (0.000589)
Observations	23,954	8,383	5,596	8,528	9,975
N subjects	1701	590	384	619	727
Pseudo R-squared	0.131	0.162	0.187	0.183	0.173
	Annual				
GDD (100s)	1.238***	1.350	1.035	1.325	1.359**
	(0.102)	(0.247)	(0.302)	(0.235)	(0.204)
KDD (100s)	0.475	0.368	0.0668*	0.242	0.190**
	(0.224)	(0.362)	(0.0967)	(0.229)	(0.147)
Precipitation (total mm)	1.002	1.003	0.991	1.002	1.003
	(0.00305)	(0.00652)	(0.00815)	(0.00634)	(0.00506)
Lag GDD (100s)	1.001	1.000	1.001	1.002*	1.002**
	(0.000755)	(0.00120)	(0.00233)	(0.00106)	(0.000904)
Lag KDD (100s)	0.998	1.004	0.998	0.994*	0.991***
	(0.00202)	(0.00426)	(0.00649)	(0.00358)	(0.00262)
Lag Precipitation (total mm)	1.000 (0.000320)	1.000 (0.000438)	1.000 (0.00111)	1.001** (0.000433)	1.001*** (0.000390)
Observations	23,954	8,383	5,596	8,528	9,975
N subjects	1701	590	384	619	727
Pseudo R-squared	0.131	0.163	0.193	0.182	0.172

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, two lags and one lead, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Effect of Climate Variables on Year of Entry, by Education Level with Debt at Time of Entry

VARIABLES	(1) Entry Debt, All Education Levels	(2) Illiterate	(3) Secondary School	(4) Secondary and Above	(5) Some Education
			Kharif		
GDD (100s)	1.054	0.385*	1.919*	2.464**	2.190***
	(0.194)	(0.189)	(0.645)	(0.931)	(0.659)
KDD (100s)	0.0243***	0.276	0.00831	0.00590*	0.0134**
	(0.0328)	(0.609)	(0.0279)	(0.0170)	(0.0256)
Precipitation (total mm)	1.010**	1.004	1.004	1.012	1.014
	(0.00476)	(0.0102)	(0.0110)	(0.0102)	(0.00920)
Lag GDD (100s)	1.004*	1.004	1.002	1.003	1.003
	(0.00212)	(0.00301)	(0.00281)	(0.00230)	(0.00261)
Lag KDD (100s)	0.981**	0.974***	0.969**	0.968**	0.981**
	(0.00792)	(0.00948)	(0.0135)	(0.0126)	(0.00879)
Lag Precipitation (total mm)	1.002**	1.001	1.004***	1.003***	1.003***
	(0.000930)	(0.00112)	(0.00126)	(0.00102)	(0.00110)
Observations	9,320	3,701	3,572	4,051	5,619
N subjects	665	253	264	301	412
Pseudo R-squared	0.180	0.258	0.286	0.265	0.204
			Annual		
GDD (100s)	1.347*	1.190	1.131	1.524	1.658**
	(0.229)	(0.444)	(0.401)	(0.437)	(0.347)
KDD (100s)	0.248	0.328	0.162	0.0796*	0.0947**
	(0.240)	(0.524)	(0.268)	(0.110)	(0.0980)
Precipitation (total mm)	1.007	1.001	0.996	1.005	1.011
	(0.00601)	(0.0108)	(0.0111)	(0.00782)	(0.00797)
Lag GDD (100s)	1.001	0.998	1.002	1.003***	1.002
	(0.00115)	(0.00201)	(0.00148)	(0.00115)	(0.00123)
Lag KDD (100s)	0.997	1.005	0.988*	0.987**	0.994
	(0.00490)	(0.00914)	(0.00722)	(0.00640)	(0.00523)
Lag Precipitation (total mm)	1.001	1.000	1.003***	1.002***	1.002***
	(0.000560)	(0.000581)	(0.000467)	(0.000461)	(0.000540)
Observations	9,320	3,701	3,572	4,051	5,619
N subjects	665	253	264	301	412
Pseudo R-squared	0.176	0.244	0.273	0.251	0.199

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, two lags and one lead, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12. Effect of Climate Variables on Year of Entry, by Education Level and No Entry Debt

VARIABLES	(1) No Entry Debt, All Education Levels	(2) Illiterate	(3) Secondary School	(4) Secondary and Above	(5) Some Education
			Kharif		
GDD (100s)	0.875	0.932	1.150	1.043	0.787
	(0.130)	(0.268)	(0.403)	(0.272)	(0.159)
KDD (100s)	3.566*	1.080	762.7***	306.1***	11.15
	(2.521)	(2.250)	(1,901)	(608.1)	(19.82)
Precipitation (total mm)	0.996	0.996	1.002	0.999	0.996
	(0.00465)	(0.00759)	(0.00857)	(0.00622)	(0.00635)
Lag GDD (100s)	1.002*	1.000	1.001	1.002	1.002
	(0.00127)	(0.00283)	(0.00253)	(0.00225)	(0.00186)
Lag KDD (100s)	0.998	0.995	1.002	0.997	0.996
	(0.00472)	(0.00725)	(0.00957)	(0.0110)	(0.00782)
Lag Precipitation (total mm)	1.000	0.999	1.000	1.001*	1.000
	(0.000571)	(0.00100)	(0.000775)	(0.000704)	(0.000714)
Observations	13,895	4,381	4,837	5,781	9,514
N subjects	992	319	348	417	673
Pseudo R-squared	0.142	0.164	0.228	0.216	0.174
			Annual		
GDD (100s)	1.097	1.386	1.181	1.065	1.103
	(0.101)	(0.315)	(0.297)	(0.213)	(0.165)
KDD (100s)	0.895	0.220*	3.453	2.315	0.453
	(0.480)	(0.187)	(5.145)	(2.892)	(0.423)
Precipitation (total mm)	0.999	1.003	0.999	0.997	0.998
	(0.00316)	(0.00603)	(0.00788)	(0.00636)	(0.00434)
Lag GDD (100s)	1.001	1.000	1.004**	1.003**	1.003**
	(0.000836)	(0.00148)	(0.00138)	(0.00130)	(0.00119)
Lag KDD (100s)	0.999	1.011*	0.990*	0.992	0.992**
	(0.00243)	(0.00591)	(0.00547)	(0.00526)	(0.00370)
Lag Precipitation (total mm)	1.000	1.000	1.000	1.001	1.000
	(0.000438)	(0.000424)	(0.000765)	(0.000677)	(0.000579)
Observations	13,895	4,381	4,837	5,781	9,514
N subjects	992	319	348	417	673
Pseudo R-squared	0.142	0.177	0.227	0.210	0.177

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, two lags and one lead, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13. Robustness Checks: Control Variables*

VARIABLES	(1) No Controls	(2) Plus Individual Controls	(3) Plus District Strata	(4) Plus origin state FE	(5) Plus year FE	(6) Plus Time Trend	(7) Plus State-Time FE
GDD (100s)	0.929*	0.934	1.005	1.005	0.939	0.939	0.939
	(0.0376)	(0.0488)	(0.153)	(0.153)	(0.101)	(0.101)	(0.101)
KDD (100s)	1.696	1.716	0.373	0.373	1.448	1.448	1.448
	(0.798)	(1.107)	(0.335)	(0.335)	(0.644)	(0.644)	(0.644)
Precipitation	1.000	1.000	1.001	1.001	1.002	1.002	1.002
(total mm)	(0.00142)	(0.00179)	(0.00481)	(0.00481)	(0.00263)	(0.00263)	(0.00263)
N subjects	1875	1701	1701	1701	1701	1701	1701
Pseudo R-squared	0.00317	0.00354	0.00722	0.00722	0.131	0.131	0.131
Observations	26,366	24,127	24,127	24,127	24,127	24,127	24,127
Individual Controls	N	Y	Y	Y	Y	Y	Y
District Strata	N	N	Y	Y	Y	Y	Y
Origin State FE	N	N	N	Y	Y	Y	Y
Year FE	N	N	N	N	Y	Y	Y
Time Trend	N	N	N	N	N	Y	Y
State-Time Trend	N	N	N	N	N	N	Y

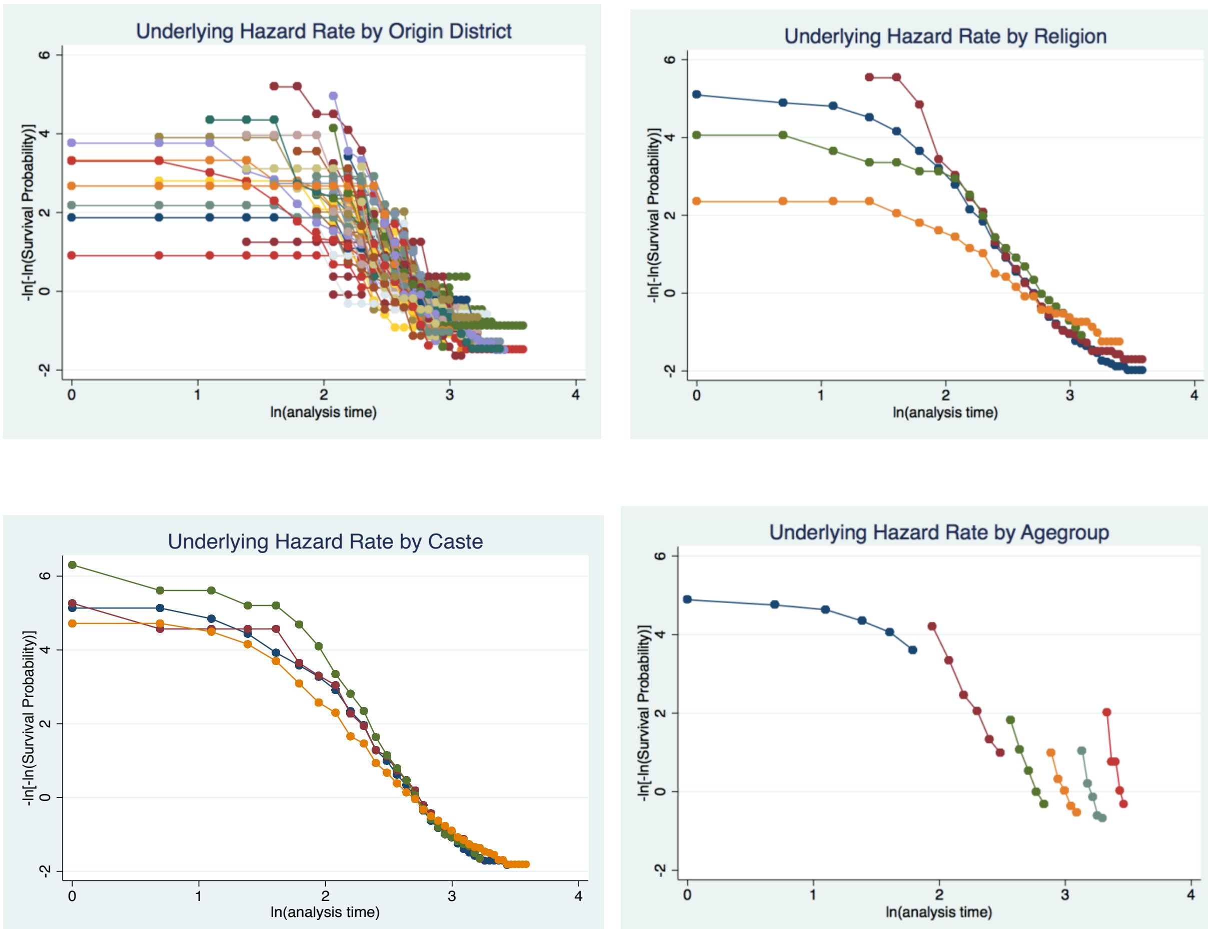
*All specifications use kharif climate variables, precipitation squared, and degree day-precipitation interactions. District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14. Robustness Checks: Lags and Leads

			Kharif			
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	No lags	1 lag	1 lag 1 lead	2 lags	2 lags 1 lead	3 lags 1 lead
GDD (100s)	0.939	0.968	0.961	0.953	0.941	0.954
	(0.101)	(0.108)	(0.105)	(0.124)	(0.122)	(0.122)
KDD (100s)	1.448	1.048	1.081	1.071	1.116	0.847
	(0.644)	(0.598)	(0.641)	(0.629)	(0.680)	(0.541)
Precipitation	1.002	1.002	1.002	1.001	1.001	1.002
(total mm)	(0.00263)	(0.00282)	(0.00316)	(0.00331)	(0.00349)	(0.00346)
Lag GDD (100s)		1.002**	1.002**	1.002***	1.002**	1.002*
		(0.000852)	(0.00104)	(0.000826)	(0.000983)	(0.00102)
Lag KDD (100s)		0.993**	0.992*	0.993*	0.993*	0.991**
		(0.00362)	(0.00399)	(0.00353)	(0.00383)	(0.00432)
Lag precipitation		1.001	1.001	1.001*	1.001	1.000
(total mm)		(0.000409)	(0.000524)	(0.000394)	(0.000487)	(0.000510)
Observations	24,127	24,052	24,039	23,967	23,954	23,852
N subjects	1701	1701	1701	1701	1701	1701
Pseudo R-squared	0.131	0.132	0.131	0.132	0.131	0.131
			Annual			
GDD (100s)	1.204**	1.213**	1.246***	1.207**	1.238***	1.258***
	(0.0957)	(0.0952)	(0.102)	(0.0958)	(0.102)	(0.112)
KDD (100s)	0.617	0.585	0.524	0.517	0.475	0.442*
	(0.272)	(0.266)	(0.240)	(0.242)	(0.224)	(0.218)
Precipitation	1.002	1.002	1.002	1.001	1.002	1.002
(total mm)	(0.00298)	(0.00307)	(0.00299)	(0.00306)	(0.00305)	(0.00316)
Lag GDD (100s)		1.001	1.001	1.001	1.001	1.001
		(0.000693)	(0.000704)	(0.000729)	(0.000755)	(0.000764)
Lag KDD (100s)		0.999	0.999	0.999	0.998	0.999
		(0.00177)	(0.00184)	(0.00197)	(0.00202)	(0.00216)
Lag precipitation		1.000	1.000	1.000	1.000	1.000
(total mm)		(0.000317)	(0.000318)	(0.000318)	(0.000320)	(0.000327)
Observations	24,127	24,052	24,039	23,967	23,954	23,852
N subjects	1701	1701	1701	1701	1701	1701
Pseudo R-squared	0.131	0.132	0.131	0.132	0.131	0.131

Includes interaction between GDD and precipitation and KDD and precipitation to capture the augmenting impact of rainfall on the positive impact of GDD and the dampening impact of rainfall on the negative impact of KDD, precipitation squared (to capture diminishing effects), year FE, district FE, state*time trends, district and age strata, and individual time invariant controls. Standard errors are clustered at the district level and presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 4: Baseline Hazard Rates by Origin District, Religion, Caste, and Age Group



Baseline hazard rates by origin district, religion, caste, and age group. These figures show that each of these groups have different baseline probabilities of entry into sex work in a given year. Including these variables in the estimated model is necessary for isolating the impact of climate variables as well as possible.

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