Abstract

The multifaceted determinants of suicide have long been studied by psychologists and sociologists, but only a small and more recent literature in economics has contributed to understanding this phenomenon. We utilize a comprehensive set of suicide data from India, one of the countries most publicly struggling with rising suicide rates today, to look for evidence of economically motivated suicide. Using state-level panel data on suicide rates between the years 1967 and 2013 and exogenous variation in climate, we (a) identify the causal effect of variations in temperature and precipitation on suicide rates across the country; and (b) find empirical support for an economic channel through which these shocks affect suicide. We employ a fixed effects framework to show that temperature has a positive and significant effect on suicide, but only during India’s main agricultural growing season, when high temperatures also lower crop yields. For growing season days above 10°C, a 1°C increase in daily temperature causes an additional 370 suicides. The magnitude and robustness of this result, in tandem with additional mechanism tests, suggests the presence of an important economic component to suicide. Contrary to public discussions of drought and suicide in India, growing season precipitation has a minimal impact on suicide rates. We find evidence that both temperature and precipitation effects operate, at least in part, through economic channels. Our results provide some justification for the development of suicide prevention policies that ameliorate the negative economic shocks suffered by agriculture-dependent households in India, such as debt relief. We also contribute to a growing literature on the social and economic impacts of climate change. Suicide prevalence, an indicator of severe hardship, may capture facets of welfare previously unmeasured in the climate change literature, and thus suggests a new avenue through which we can assess the climate-welfare relationship.
1 Introduction

That suicide may often be consistent with interest and with our duty to ourselves, no one can question, who allows that age, sickness, or misfortune, may render life a burden, and make it worse even than annihilation. I believe that no man ever threw away life, while it was worth keeping. - Hume

Humans have long debated the rationality and morality of suicide. Stoic philosophy regarded suicide as noble when chosen through a deliberative process, placing rational decision-making at the heart of the act (Seidler 1983). Monotheistic religions, contrarily, generally view suicide as morally reprehensible, and most current legal systems render it a crime. Since the seminal work of Durkheim (1951), modern psychologists and sociologists have balanced the multiplicity of causes behind the choice to take one's own life, emphasizing to varying degrees moral, cultural and often economic factors. However, only recently, and rarely, has the economic rationality of suicide been modeled and empirically tested by economists (Becker and Posner 2004, Hamermesh and Soss 1974). In this paper, we utilize a comprehensive set of suicide data from India, one of the countries most publicly struggling with rising suicide rates today, and ask: how economic is suicide?

India’s suicide death rate has nearly doubled since 1980. One fifth of global suicides occur in India: at least 135,000 lives were lost to suicide in 2010. Suicide amongst the rural population has gained particular academic and media attention; recent data from India’s National Crime Records Bureau (NCRB) shows that in some states the share of suicides committed by farmers currently exceeds 75%, and has risen over the last decade. Blame is often placed on a range of agrarian, and clearly economic, changes. Nearly all cited causes of recent suicide trends are agricultural in nature, and range from trade liberalization of the economy in the 1990s to farmer debt induced by high input costs of Green Revolution technologies like fertilizer and high-yield variety seeds (Mohanty 2005). A common causal mechanism in these arguments is that shocks to agricultural profitability, especially drought events and crop failure, induce suicide as a coping response to the economic stress placed on farming households (Deshpande 2002, Gruère and Sengupta 2011). While India has slowly been urbanizing over time, economic welfare continues to be closely tied to agricultural outcomes. The fact that a majority of Indian suicides are committed by ingestion of pesticides (WHO 2014), which some have argued is a symbolic act (Patel 2007), further suggests that these deaths are occurring as responses to agricultural

1Recent media coverage of Indian suicides include a 2014 article in The Guardian titled “India’s farmer suicides: are deaths linked to GM cotton?”, 2013 coverage by BBC News asking “Indian farmers and suicide: How big is the problem?”, a 2006 New York Times article titled “On India’s Farms, a Plague of Suicide”, and hundreds of pages of coverage in an array of Indian media outlets.
hardship.

However, it is not empirically clear that economic strife is behind many Indian suicides. In 2010, data from the NCRB show that only 4% of total suicides were attributed to bankruptcy or poverty, while 24% were due to family problems and 19% to physical or mental illness. Agriculture’s role in particular is debatable: while some states have exceptionally high farmer suicide rates, the mean share of male suicides committed by farmers over the last decade is only 15%, and for females it is only 4%. While these numbers are likely poorly measured and perhaps biased, they cast doubt on the prominence of economic motivations. Moreover, existing evidence of an agricultural mechanism is anecdotal (Mohanty, 2005; Patel, 2007), correlational (Gruère and Sengupta, 2011), or covers only a small region of the country (Hebous and Klonner, 2014). In this paper, we use national state-level panel data on suicide rates between the years 1967 and 2013 and exogenous variation in climate to first identify a causal effect of temperature and precipitation on suicide rates, and then to seek empirical support for an economic channel through which these shocks drive suicide.

We find that temperature has a positive and significant effect on suicide, but only during India’s main agricultural growing season. The magnitude of this result, robust to a variety of specifications, suggests the presence of an important economic component to suicide. To further explore the relevance of agriculture to suicide prevalence, we use yield data to provide suggestive “fingerprinting” evidence (Hsiang, Burke, and Miguel, 2013) of the shared pattern between suicides and yield losses, as they relate to temperature. We find that yields and suicides have matching responses: hot days during the growing season both damage yields (as has been shown by Guiteras, 2009 and Burgess et al., 2014) and increase suicide rates, while non-growing season heat has a minimal effect on both outcomes. In a final test of the plausibility that economic motives drive our reduced form results, we use cross-sectional patterns in geographic heterogeneity of effects. We show that states with more severe histories of farmer suicide have stronger responses to temperature, and that states with higher crop losses due to temperature also exhibit more suicides under heat stress. Contrary to common wisdom, growing season precipitation has a very minimal impact on suicide rates, despite generating yield gains, while drought appears insignificant. We explore possible reasons for this result, showing that we may be underpowered to identify an agriculturally-driven impact of rainfall on suicides, given the small effect rain has on yields relative to temperature, a finding consistent with existing literature (Burgess et al., 2014; Guiteras, 2009).

We conclude that over our sample time period in India, there appears to be a strong economic
component to suicide, exhibited by significant impacts of exogenous climate shocks, particularly hot
temperatures, operating through agricultural channels. Our results contribute to two bodies of ex-
isting research, with distinct policy implications. First, we add to a the literature on the economic
determinants of suicide, supporting existing studies that also find evidence of economic motives. Our
findings provide some justification for the development of suicide prevention policies that ameliorate
the negative economic shocks suffered by agriculture-dependent households in India, such as debt re-
lief. Second, we contribute to a growing literature on the welfare impacts of climate change. Suicide
prevalence, an indicator of severe hardship, may capture facets of welfare previously unmeasured in the
cclimate change literature, and thus suggests a new avenue through which we can assess the climate-
welfare relationship. Our suicide findings can contribute to an accurate assessment of the impacts of
cclimate variability on human welfare, a critical step in the design of policy responses to climate change.

In this paper, we use the term climate in reference to observations of temperature and precipitation.
While climate is generally defined as the long-run distribution of climatic variables and not to short-run
observations, this distribution is inherently composed of short-run realizations. Societies experience
and respond to these short-lived outcomes, implying the frequency of these events is an important
economic facet of the climate (Burke, Hsiang, and Miguel, 2014). This is a view particularly relevant to
anthropogenic climate change: as the distribution of climatic variables shifts, the frequency with which
a population experiences a given climate observation (e.g. a hot day) also changes. Understanding the
impacts of these short-run events is therefore critical to understanding how societies are impacted by
cclimate change.

The paper proceeds as follows: we briefly review relevant literature in Section 2 outline a conceptual
framework in Section 3 and describe our data in Section 4. Section 5 details our empirical strategy,
Section 6 shows our results, and we conclude in Section 7.

2 Previous Literature

The causes of suicide are strongly debated across the social sciences, and the extent to which economic
welfare plays a role has remained unclear. In a review of the sociological literature, Stack (2000) de-
scribes inconsistent findings on the relationship between unemployment and suicide, emphasizing that
studies rarely control for many unemployment covariates that also affect suicide. Similarly, Rehkopf
and Buka (2006) review “widely divergent” findings on the impacts of economic variables on suicide
in the psychological literature, again focusing on methodological challenges. To our knowledge, only a small number of economists have sought to use theoretical and empirical tools to rigorously address this question.

Hamermesh and Soss (1974) were the first to directly model and empirically explore suicide in economics, using time series and cross-sectional variation in the U.S. to argue that suicide rates increase with aggregate measures of unemployment. Becker and Posner (2004) further developed an economic theory of suicide, and a small body of recent empirical work has sought to better identify the role of economics. However, despite the fact that 75% of suicides occur in low-income countries (WHO, 2014), this literature is almost exclusively focused on OECD nations (e.g. Andres (2005); Inagaki (2010)). Studies generate conflicting results (Andres, 2005; Botha, 2012), and tend to employ time series and cross sectional data instead of panel (Lloyd and Yip, 2001; Snipes, Cunha, and Hemley, 2012). Panel studies that do exist identify macroeconomic impacts, such as business cycles, rather than microeconomic shocks (Botha, 2012; Piérard and Grootendorst, 2014; Snipes, Cunha, and Hemley, 2012). We contribute to this literature by utilizing panel data in India, focusing explicitly on the importance of and challenges involved in using exogenous variation to isolate the impact of microeconomic variation on suicide.

India’s suicide trends have garnered widespread media and political attention, complemented by a large body of academic work. While much has been written on the influence of economics and agriculture on Indian suicide, nearly all papers use qualitative methods to detail particular circumstances of rural suicides in isolated areas of India (Deshpande, 2002; Herring, 2008; Mohanty and Shroff, 2004; Mohanty, 2005; Rao and Gopalappa, 2004; Sarma, 2004). While these studies are valuable, they have low external validity, and without quantitative results are difficult to integrate into policy. In contrast, Hebous and Klonner (2014) use panel data for two states over 6 years and an instrumental variables framework to estimate the impact of poverty on suicide. While they argue that poverty increases the male suicide rate, their results are significant for only one of two states, and the climate variables used as instruments are unlikely to satisfy the exclusion restriction (Hsiang, Burke, and Miguel, 2013). The only national-level studies we have identified are descriptive in nature (Nagaraj, 2008) or make inferences based on cross-sectional correlations (Jonathan Kennedy, 2014). In this paper, we use data covering all of India over nearly 50 years and employ a fixed effects empirical strategy to identify causal effects of exogenous shocks to income and suicide. While we do not claim to directly identify economic suicide motives, we use a variety of techniques to assess the plausibility that our reduced form results
operate through an agricultural, and hence economic, channel.

Our work also contributes to the literature on the welfare impacts of climate change. The startling pervasiveness of suicide makes it a singularly important component of the well-known impact of climate on mortality (Barreca et al., 2013; Burgess et al., 2014; Deschênes and Greenstone, 2011): each year, suicide claims over 800,000 lives globally and is the second most common cause of death for people aged 15 to 29. The majority of these deaths occur in low- and middle-income countries, many of which, like India, have seen suicide numbers rise in recent years (WHO, 2014). Although a growing literature on climate and violent conflict exists, reviewed in Burke, Hsiang, and Miguel (2014), Basyan et al. (2014) is the only study in economics that directly estimates the reduced form impact of climate variables on suicide rates. In contrast to our findings, the authors conclude that in Mexico, suicide does not appear to have an economic component. Our results therefore provide a second estimate in the economics literature that can help inform climate change policy, while highlighting geographic differences in economic drivers of suicide.

3 Conceptual Framing

Suicide is a multifaceted phenomenon determined by the interaction of many individual and environmental factors including mental health, social norms, beliefs, religion and, arguably, economic status. In this section, we outline the possible ways in which economic shocks may affect suicide rates in the Indian context, explicitly tracing the causal claims suggested in qualitative research and popular media. We then demonstrate how our empirical approach will allow us to use data on climate variability and agricultural output to identify evidence of economic drivers of suicide, should they exist.

Economic outcomes throughout India remain closely tied to agriculture. In 2001, 57% of workers were identified as employed in agriculture and allied activities, and this share fell to only 51% in the latest national census of 2011. 70% of India’s population currently lives in rural areas (Government of India, 2011). While modern technologies such as high-yielding variety (HYV) seeds and various irrigation methods have been increasingly adopted through time, the profitability of agriculture in India, as in most nations, remains subject to unpredictable variations (Foster and Rosenzweig, 1996; Rosenzweig and Udry, 2013). Importantly, climate variability critically affects agricultural incomes, and with over 30% of the population lying below the international poverty line of US$1.25 per day,

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2The impact of climate on suicide has been identified in psychiatry (Deisenhammer, Kemmler, and Parson, 2003) and meteorology (Jessen, Jensen, and Steffensen, 1998).
climate shocks can have dire consequences for households relying on agriculture. The probability that any individual will contemplate, attempt or commit suicide depends on many, often unobservable, factors. However, negative income shocks like those induced by agricultural income variability in India may increase the likelihood for some individuals by increasing stress (Chemin, De Laat, and Haushofer, 2013), or by exacerbating existing risk factors such as family challenges or mental and physical health (Rehkopf and Buka, 2006; Stack, 2000).

To seek evidence of economic motivations of suicide, we exploit random variation in a central determinant of economic outcomes in India: climate variability. We identify the impact of economically meaningful climate shocks - that is, climate outcomes that we demonstrate have substantial causal impacts on agricultural yield values - on suicide rates, looking for evidence that the same types of climate variations that reduce agricultural income are those that elevate suicide rates. We refrain from an instrumental variables (IV) approach in which climate variables instrument for crop yields, as the exclusion restriction is unlikely to hold due to the direct psychological impacts that climate factors plausibly have on suicide rates (Anderson et al., 1999; Davidson, Putnam, and Larson, 2000; Jessen, Jensen, and Steffensen, 1998; Lövheim, 2012; Seo, Patrick, and Kennealy, 2008). While many factors unmeasured in our analysis undoubtedly affect suicides in India, the exogeneity of climate realizations in any given location allow us to identify a causal impact of climate on suicide, and the distinction between economically meaningful and economically unimportant climate outcomes allows us to uncover an agricultural channel through which these climate variations drive suicides.

4 Data

We combine suicide and climate data at the state level for the years 1967-2013. To compare suicide and yield responses to climate, we use an agricultural yield dataset at the district level for the period 1956-2000, combined with district-level climate data for the same years. Summary statistics for key variables of interest are provided in Table 1.

4.1 Suicides

Suicide records in India are publicly available only at the state level. These data are in the “Accidental Deaths and Suicides in India” report, published annually by the Indian National Crime Records Bureau (NCRB) since 1967 for 27 of India’s 29 states and 5 of its 7 Union Territories. The dataset includes
total number of state suicides per year, with gender, occupation and cause of death information available after 2001. We calculate suicide rates as the number of total suicides per 100,000 people, with population data linearly interpolated between Indian censuses. We do not exploit data on occupation or gender, as this information is available only after 2000. Thus, we are measuring the overall suicide rate, which will include farmers, non-farmers, and the unemployed.

Deaths in general are under-reported in India (Burgess et al., 2014), and the suicide data provided by the NCRB are particularly problematic in this regard. The data are aggregated from district police reports. Since attempted suicide is a criminal offense punishable under the Indian Penal Code, there is likely to be significant under-reporting of suicide as a cause of death, as surviving family members may experience social stigma from the criminality of the event. As evidence of this, the NCRB reports 135,000 suicides in India in 2010, while data from a randomly sampled survey of cause of death estimates the 2010 value at 187,000 (Patel et al., 2012). This under-reporting is likely uncorrelated with temperature and precipitation (otherwise, we would have to argue that hotter or drier conditions induce better reporting, which seems implausible). Thus, our estimates of the response of suicide to climate provide lower bounds on the true marginal effect, due to attenuation bias.

The evolution over time and space of state level suicide rates in India during our sample period is shown in Figure 1; darker shades indicate higher suicide rates. There is clear spatial heterogeneity, with southern India experiencing the highest suicide rates and largest increases over time. These geographic differences inform our empirical strategy, which relies on within-state variation in order to avoid conflation of climate impacts with unobservables, such as cultural norms, political structures, and religious influences. Moreover, we account for regional differences in time trends, due to clearly distinct patterns over time across India.

4.2 Climate

Both Deschenes and Greenstone (2011) and Burgess et al. (2014) emphasize that estimating the relationship between mortality and climate requires daily temperature data, as the relationship is nonlinear and annual average temperatures obscure such nonlinearities. While existing studies on temperature and suicide in the epidemiology literature do not explore nonlinearities, there are two reasons why they are likely to occur. First, the growing literature on climate and interpersonal conflict reviewed by

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3 As a point of reference, suicide rates in the United States are currently approximately 12.5 per 100,000.
4 The only existing paper in the economics literature identifying climate’s impact on suicide is Basyan et al. (2014). The authors do not allow for nonlinear temperature effects.
Burke, Hsiang, and Miguel (2014) often identifies nonlinearities in the effect of temperature on violent crime. If we view suicide as a type of violence against oneself, it’s likely that a similar relationship exists here. Second, Schlenker and Roberts (2009), among others, have identified a strongly nonlinear response of staple crop yields to temperature. If suicide in India is indeed related to agricultural productivity, then capturing this nonlinearity is critical.

Daily weather data are not publicly available for India with adequate geographic and temporal coverage. Thus, we rely on the temperature data used by Guiteras (2009) and Burgess et al. (2014): the National Center for Environmental Protection (NCEP) gridded daily dataset, a reanalysis product that provides observations in a 1°×1° grid. These data are produced by NCEP and the Climatic Research Unit at the University of East Anglia and include daily mean temperature for each grid over our entire sample period. Because there are multiple grid cells per state, we aggregate grids to state-level daily temperature observations using an area-weighted average.

To convert daily temperature into annual observations without losing intra-annual variability in daily weather, we use the agronomic concept of degree days. Degree days are calculated as follows, where \( t^* \) is a selected cutoff temperature value and \( t \) is a realized daily temperature value:

\[
D_{t^*}(t) = \begin{cases} 
0 & \text{if } t \leq t^* \\
t - t^* & \text{if } t > t^* 
\end{cases}
\]  

Degree days allow temperature to affect an outcome variable only once its value surpasses the threshold \( t^* \). When degree days are summed over a time, regressing an outcome on cumulative degree days \( \sum_{t=1}^{T} D(t) \) imposes a piecewise linear relationship, in which the outcome response has zero slope for all temperatures less than \( t^* \). While a body of literature identifies biologically-determined cutoffs \( t^* \) for a variety of major crops, there is no empirical support to draw on in selecting \( t^* \) for suicides. Thus, we use a range of plausible cutoffs based on the distribution of our temperature data to estimate a flexible piecewise linear function that imposes minimal structure on the response function.

Because reanalysis models are less reliable for precipitation data, and because nonlinearities in precipitation that can’t be captured with a polynomial appear to be less consistently important both in the violent crime literature (Burke, Hsiang, and Miguel 2014) and in the agriculture literature (Schlenker and Roberts 2009), we use the University of Delaware monthly cumulative precipitation data to compliment daily temperature observations (Willmott and Matsuura 2014). These data are gridded at a 0.5°×0.5° resolution, with observations of total monthly rainfall spatially interpolated
between weather stations. We again aggregate grids up to states using area-based weights.

4.3 Agriculture

We use agricultural data from Duflo and Pande (2007), who provide district-level annual yield estimates for major crops between 1956 and 2000, compiled from Indian Ministry of Agriculture reports and other official sources. These data cover 271 districts in 13 major agricultural states, although they omit Kerala and Assam, two large agricultural producers with high rates of suicide. We match these district data to the same climate data described above, area-weighting over districts instead of states. We use this merged climate-yield dataset to generate a response function of log annual yield values of five major crops (in constant Indian Rupees) to temperature and rainfall, allowing us to identify similarities and differences in how suicides and yields are impacted by climatic shocks. These data are limited in their ability to identify heterogeneity of suicide impacts, as they cover only 13 states, do not extend past 2000 and do not contain recent irrigation data. However, they allow for more precise estimation of impacts, given their high spatial resolution.

5 Empirical Strategy

5.1 Reduced form

To identify the impact of temperature and precipitation on annual suicide rates, we estimate two versions of a panel fixed effects model in which the identifying assumption is the exogeneity of within-state annual variation in degree days and cumulative precipitation. Heterogeneity in suicide rates and trajectories across states, due to an interplay between unobservable cultural, political and economic factors, implies that cross-sectional variation in climate is endogenous. Thus, we use state and year fixed effects with regional time trends to control for time-invariant state-level unobservables, national-level temporal shocks and region-specific time trends.

There is minimal precedent for the functional form of suicide’s relationship to climate. Our first estimation approach therefore employs the most flexible model our data will allow, and one that is consistent with the broader climate impacts literature. We use a piecewise linear response function

\footnote{1\% of the observations in all precipitation variables were Winsorized (Hastings Jr et al., 1947) on the right tail only, due to the presence of a small number of outliers. Results are robust to different levels of Winsorizing, and to leaving the data complete.}

\footnote{It is important to keep in mind that while they have significant overlap, our agriculture and suicide data cover slightly different years and have distinct spatial coverage.}
with respect to temperature, with kinks at $10^\circ C$ intervals, and a cubic polynomial function of cumulative precipitation. To capture the distinct impact of economically meaningful climate variation, we separately identify the temperature and precipitation response functions by agricultural seasons. Crop seasonality in India is determined by the onset and withdrawal of the southwest monsoon, which signals the beginning and close of the main growing season, called the *kharif*. Monsoon rainfall arrives on the southern coast of India around June 1st and moves northward through the summer, withdrawing in a reverse geographic pattern. For simplicity and to be consistent with prior work on Indian agriculture (Auffhammer, Ramanathan, and Vincent 2006; Duflo and Pande 2007; Guiteras 2009), we define the growing season as June 1st through September 30th for all states. However, results are robust to using state-specific growing season dates derived from long-run average monsoon patterns reported by the Indian Meteorological Department.

Let $suicide\_rate_{it}$ be the number of suicides per 100,000 people in state $i$ in year $t$, $s \in \{1, 2\}$ be the season (growing and non-growing). Then $T_{idst}$ is state $i$’s temperature in $^\circ C$ on day $d$ in season $s$ in year $t$, and $P_{imt}$ is cumulative precipitation during month $m$ in season $s$ in year $t$. We use $k = 4$ bins of temperature, each of width $10^\circ C$, with the final bin containing all degree days above $30^\circ C$. Our main empirical model is thus:

$$suicide\_rate_{it} = \alpha + \sum_{s=1}^{2} \sum_{k=1}^{4} \beta_{ks} \sum_{d \in s} T_{idst} + \sum_{s=1}^{2} \lambda_{1s} \sum_{m \in s} P_{imt} + \sum_{s=1}^{2} \lambda_{2s} \sum_{m \in s} P_{imt}^2 + \sum_{s=1}^{2} \lambda_{3s} \sum_{m \in s} P_{imt}^3 + \delta_i + \eta_t + \tau_r t + \varepsilon_{it}$$  \hspace{1cm} (2)

Equation (2) generates a piecewise linear response function for temperature, with four distinct temperature slope parameters in each season. State fixed effects $\delta_i$ account for time-invariant unobservables at the state level, while year fixed effects $\eta_t$ account for India-wide time-varying unobservables. In most specifications, we include region-by-year time trends $\tau_r t$ to control for differential regional trends in suicide driven by time-varying unobservables. For these suicide regressions, we define our regions using a classification system derived by Nagaraj (2008), which groups states based on the prevalence of suicide as well as trends in total suicides and farmer suicides through time. For yield regressions, we follow Guiteras (2009) in dividing states into four geographically-determined regions. Results are also robust to alternative regional definitions, and in particular are upheld when we apply the same regions

\[Results are very similar, yet less precise, when we use temperature bins of width 5^\circ C. These results are available upon request.\]

\[These results are available upon request.\]
to both the yield and suicide data. These regional trends absorb much of the variation in suicide rates, so we show results for models with and without the $\tau_r t$ term. Our identifying assumption is that, conditional on $\delta_i$, $\eta_t$, and $\tau_r t$, variations in daily temperature and monthly rainfall are as good as random.

Separately for each season, Equation 2 allows us to identify each $\beta_k$ slope parameter. The marginal effects are interpreted as follows: $\hat{\beta}_k$ estimates the change in the annual number of suicides per 100,000 people induced by one day in bin $k$ becoming $1^\circ C$ warmer, estimated separately for each season $s$. This annual response to a daily forcing variable is similar to that estimated and described in Deryugina and Hsiang (2014). The $\hat{\lambda}$ parameters estimate a polynomial response function of the annual suicide rate to an additional millimeter of rainfall, again estimated seasonally. Due to likely correlation between errors within states, we cluster standard errors at the state level. This strategy assumes spatial correlation across states in any time period is zero, but flexibly accounts for within-state, across-time correlation.

A secondary specification that we employ to improve readability of tables, reduce the statistical requirements placed on the data, and run heterogeneity tests, is a simple cumulative degree days model. We estimate the following equation, where $DD_{X, idt}$ is degree days above a threshold of $X^\circ C$. We test robustness of results for degree day thresholds of $X = 10, 15, 20$ and $25^\circ C$.

\[
suicide\ rate_{it} = \alpha + \sum_{s=1}^2 \beta_s \sum_{d \in s} DD_{X, idt} + \sum_{s=1}^2 \lambda_{1s} \sum_{m \in s} P_{imt} + \sum_{s=1}^2 \lambda_{2s} \sum_{m \in s} P_{imt}^2 + \sum_{s=1}^2 \lambda_{3s} \sum_{m \in s} P_{imt}^3 + \delta_i + \eta_t + \tau_r t + \varepsilon_{it} \tag{3}
\]

This model is also piecewise linear in temperature, but assumes a zero marginal response of suicide to temperature for daily values below $X^\circ C$, and a constant linear response with a slope of $\beta_s$ for temperatures above $X$ in season $s$. $\hat{\beta}_s$ estimates the change in the annual suicide rate caused by a one degree increase in daily temperature, conditional on temperature being above $X^\circ C$.

Note that both of these specifications do not include lagged climate variables, consistent with literature on climate and mortality in India (Burgess et al., 2014). However, if climate shocks lower yields during the growing season in year $t$, suicide in year $t + 1$ could plausibly be affected. To account for this possibility, we run robustness checks including up to two years of lags in temperature and precipitation variables. Figure 2 in the Appendix shows that lagged coefficients are generally not significant, while the impacts of contemporaneous climate remain. We also check for the presence of cumulative climate shocks (e.g. two consecutive years of low rainfall) in Section 6 and find no evidence...
of their influence. We therefore conduct our main analyses without lagged variables. However, we acknowledge that lagged effects may be important, but simply unidentifiable in our data.

5.2 The role of agriculture

With ideal data, we would estimate separate response functions for farmers and non-farmers to isolate the importance of an agricultural channel. Because our data do not provide the occupation of suicide victims prior to 2001 (and because using only post-2001 data at the state level leaves us with an exceptionally small sample size in which no climate effects are statistically significant), we utilize a variety of other methods to investigate the validity of the oft-cited agricultural mechanism. The primary approach we take is to compare the significance and magnitude of each coefficient $\beta_k$ in Equation 2 across seasons. Temperatures and rainfall in June through September have been shown to be most critical for agricultural productivity (Burgess et al., 2014; Guiteras, 2009), and thus should dominate the climate-suicide relationship if the agricultural channel is important. In a similar exercise, Petzer (2014) and Blakeslee and Fishman (2013) demonstrate that monsoon-season precipitation impacts civil conflict and interpersonal crime in India, respectively, more than precipitation outside the growing season. Just as they use these findings as evidence of an agricultural channel through which climate affects crime and conflict, we use our results to identify the presence of an agricultural channel for suicide.

An additional method for examining mechanisms is to “pattern match” response functions (Burke, Hsiang, and Miguel, 2014). For example, Hidalgo et al. (2010) show that the nonlinear relationship between agricultural income and rainfall in Brazil is nearly a perfect (inverse) pattern match to the relationship between land-invasion risk and rainfall. Similarly, Hsiang and Meng (2014) match the responses of conflict and income to the timing of the El Niño Southern Oscillation (ENSO), arguing results provide support for an income channel. We follow this approach by estimating Equation 2 using the log value of yield as the dependent variable in place of suicide rates, employing the Duflo & Pande agricultural data at the district level. This regression essentially replicates results in Guiteras (2009), but employs more years of data and follows a slightly different degree days methodology. We compare our response functions of suicide and yield to identify matching patterns.

Finally, we look for further support of economic motives by exploring spatial and temporal heterogeneity of impacts. For temperature shocks, we estimate a model that allows each of India’s 32 states and Union Territories to have a distinct suicide rate response function. We then look at corre-
tions between these state-level temperature responses and other variables related to agriculture, such as the ratio of farmer suicides to total suicides (for the limited years in which these data exist) and the vulnerability of state crop yields to temperature. For precipitation, we decompose the seasonal response function into monthly effects, highlighting the importance of specific months of rainfall on suicide rates. Together, season-specific regressions, pattern matching and heterogenous effects provide multiple sources of evidence that the observed impact of climate variability on suicide rates likely operates, at least in part, via economic channels.

6 Results

6.1 Temperature

Our main results for the impact of climate on suicide rates, estimated from Equation 2, are shown in Table 2. We begin by considering temperature. Temperature response functions for suicide and yield are plotted in Figure 3, with tabular results for yields shown in Table 3. Both functions have been centered at their respective means, showing the predicted annual response to a daily increase in temperature relative to mean suicides and the mean log value of yield.

Figure 3a demonstrates a clear distinction between the growing season and non-growing season response of suicide rates to temperature, with temperature in the former significantly and positively impacting suicide rates. The marginal effects in both the 10-20°C and 20-30°C bins are positive and statistically significant: for the fixed effects model, a one degree increase in daily temperature, conditional on that day being in the 10-20°C bin, increases suicides by 0.03 per 100,000 people. This is a 9.4% increase in the suicide rate per standard deviation (σ) increase in daily within-bin temperature, which increases to 10.1% when regional time trends are included. Using 2010 population values, these marginal effects imply that a 1°C increase in a day’s temperature within the 10-20°C bin causes an additional 370 suicides. The corresponding results for the 20-30°C bin are a 5.5%/σ increase and 170 more suicides per 1°C. In contrast, warm temperatures in the non-growing season have a slightly negative to zero impact on suicide rates, with only the hottest days having a significant positive marginal effect on suicides (the effect for the hottest bin in the non-growing season is 3.5%/σ). These findings are robust to our simpler degree day empirical model, as shown in Table 4. They are also consistent with related literature on suicide, as well as other types of violent conflict. In the only other empirical estimate of the reduced form impact of temperature on suicide rates, Basyan et al. (2014)
find a standardized effect of 7.4%/σ using average monthly temperatures and suicide rates in Mexico. Importantly, while our temperature result depends critically on agricultural seasonality, theirs does not; nor do other tests reveal evidence of economically-motivated suicide in Mexico. In a hierarchical Bayesian meta-analysis of the literature on climate and interpersonal conflict, Burke, Hsiang, and Miguel (2014) find an average effect of 2.4%/σ across 18 papers, each of which estimates the impact of temperature on an outcome such as rape, assault, or murder. To the extent that suicide can be seen as a type of violence related to interpersonal conflict, our estimate corresponds to a large impact, relative to the mean effect across this literature.

The distinct response of suicide to temperature in the growing and non-growing seasons is consistent with an economic story of suicide in which heat damages crops, placing pressure on farming households, in turn increasing suicide rates via heightened levels of poverty. The response of yields to temperature, shown in Figure 3b provides further evidence of such a channel. In a mirror image of the suicide response function, yields fall as growing season temperature rises. For daily temperatures in the 10-20°C bin, log annual yields fall by 1%/σ when regional time trends are included. The pattern match holds in the off-season as well, where both annual yields and suicides respond minimally, if at all, to temperature. Thus, precisely the same temperature shocks that cause agricultural losses are those that significantly increase suicide rates.

One concern with using pattern matching is that temperature may impact suicide during the growing season months only, but for reasons unrelated to agriculture. In particular, there is strong evidence that suicide is directly impacted by heat through a psychological mechanism (Basyan et al., 2014; Deisenhammer, Kemmler, and Parson, 2003). If there were few hot days outside the growing season, our model may have insufficient statistical power to identify a true off-season impact, and growing season temperature would simply be capturing the psychological effect. However, this is not empirically a concern. Many hot days do occur outside the growing season, our model may have insufficient statistical power to identify a true off-season impact, and growing season temperature would simply be capturing the psychological effect. However, this is not empirically a concern. Many hot days do occur outside the growing season (see Figure 4), and Table 2 shows that we do identify a significant off-season effect of days above 30°C, suggesting that temperature may impact suicide both through direct (psychological) and indirect (economic) channels.

6.1.1 Pattern matching in the cross-section

Reduced form results suggest the presence of an agricultural channel for the impacts of temperature on suicide. To further support this argument, we use geographic heterogeneity in impacts to show correlations between suicide responses and other key agricultural variables. We first disaggregate sui-
cide response functions by states: Figure 5 shows states colored according to their individual marginal effect, estimated from a version of Equation 3 in which growing season degree days are interacted with an indicator for each state. State coefficients are expressed as a fraction of the average treatment effect. Due to our sample size, these are noisy estimates. However, there is a clear geographic pattern that is implausibly random. Southern states (which are generally hotter, have higher suicide rates, and show and steeper trends in suicide over time) have much stronger responses to climate.

Figure 6 provides two pieces of evidence that these differential state impacts are driven, at least in part, by agriculture. First, Panel 6a shows the correlation between suicide’s response to growing season temperature and the average farmer suicide ratio, defined as the number of farmer suicides divided by the total number of suicides across all occupations, with the mean taken over the years 2001-2010 (the years for which data on occupations are available). Note that each point represents one of India’s 32 states. The positive correlation evident in this figure shows that states where farmers make up a larger share of suicides suffer higher marginal temperature effects, suggesting that agriculture is a key component of suicide’s response to temperature. Second, Panel 6b shows the correlation between each state’s yield response to growing season temperature and its suicide response to growing season temperature. Unfortunately, we can only estimate 13 distinct state-level yield responses given the coverage of our agricultural data. Nonetheless, the correlation between these 13 marginal effects of yield and suicide in Figure 6b is positive, suggesting that states with agricultural yields that are relatively more damaged by high temperatures are also states in which these temperatures increase suicide rates by a relatively substantial magnitude. Three states that have been at the center of India’s popular debates regarding agricultural influences on suicide - Maharashtra, Karnataka and Andhra Pradesh - are shown to not only have high suicide responses to temperature, but also to have high farmer suicide ratios and large negative impacts of temperature on yield.

We conclude that seasonality in response functions, pattern matching with yields, and cross-sectional evidence on the heterogeneity of impacts all suggest that temperature has a positive impact on suicide rates that is at least partially realized through agricultural losses.

The state-level differences also may be due to local suicide prevalence and/or long-run climate. There is ample evidence of the social contagiousness of suicide (Cutler, Glaeser, and Norberg 2001; Gould, Jamieson, and Romer 2003; Velting and Gould 1997), and Figure 7a shows that average rates of suicide are correlated with temperature responses, consistent with this theory. Figure 7a also shows that hotter states have steeper responses, suggesting an increased vulnerability for states with warmer average climates.
6.2 Precipitation

The precipitation response functions are shown in Figures 8a and 8b, both estimated as a cubic polynomial as in Equation 2 and as a simple linear function of cumulative rainfall for ease of interpretation. As expected, precipitation during the growing season has a positive impact on yields, while non-growing season rainfall has a statistically significant but economically minimal effect. Consistent with other literature on agricultural impacts of climate variability (Guiteras, 2009; Schlenker and Roberts, 2009), these precipitation results are smaller in magnitude than those for temperature. In the linear model, yields increase 0.9%/σ for an increase in growing season rainfall, and just 0.3%/σ for off-season rainfall. Were a simple agricultural channel to be identified for precipitation, we would expect a negative impact of growing season rainfall on suicide rates, and a minimal or zero impact in the non-growing season. Figure 8 shows a small negative growing season suicide response, despite the clear yield gains of monsoon rains. While non-growing season rainfall has a positive impact on suicide, this effect is statistically insignificant.

The null result for growing season rainfall is robust to many alternative specifications. First, Figure 2 shows that lagged rainfall has no significant effect on suicide rates, suggesting that the lack of a response is not due to a delay in the effect. Second, we create a drought indicator equal to one when annual rainfall in a state is below the 20th percentile for that state over the sample. Columns (1) through (3) in Table 5 show results for a regression including this drought variable, as well as a surplus rainfall variable indicating a year of exceptionally high rainfall. None of the coefficients on drought are significant. In results not shown, we create indicators for a state suffering two or three consecutive years of drought, but no cumulative effects are significant. Finally, we test whether irrigation is causing this null result. We use Ministry of Agriculture data to classify states as heavily irrigated if their share of crop area under irrigation ever exceeds 50% during our sample period. Figure 9 shows precipitation response functions for irrigated and rain-fed states separately, and demonstrates that accounting for irrigation does not change the findings of our main model.

There are two key reasons we may fail to identify a growing season response in suicides. First, characterizing monsoon rainfall at the state level is inherently difficult, as there are important within-state differences in monsoon arrival and withdrawal (Burgess et al., 2014). For example, some districts in states along the eastern coast of India receive a substantial portion of their rainfall in a late north-eastern monsoon period between October and December, after the close of the conventional growing season. Our need to define growing seasons at the state level due to the nature of the suicide data
may create important attenuation bias through measurement error. Figure 10 suggests measurement error may be at play: this plot of monthly rainfall effects suggests a consistently negative, yet often insignificant, impact of rainfall on suicide rates during the main growing season months. Second, many suicide victims whose incomes are tied to agriculture may also have crop insurance, the payouts of which are nearly always tied to rainfall in India (Giné, Townsend, and Vickery, 2007). Even though low precipitation years clearly damage yields, agriculturally-dependent households may receive sufficient insurance funds to mitigate negative income impacts, ameliorating a potential suicide response. While we do not formally address the impact of insurance on suicide in this paper, we see this as a fruitful area for subsequent work. In sum, our results appear to contradict the dominant focus on drought in most media coverage of suicide in India.

7 Discussion

In this paper we address the long-debated question of the role of economics in suicide, using exogenous variation in climate to identify shocks to income and suicide in a developing country context. While we cannot precisely identify the effect of income on suicide rates, we estimate the causal effect of exogenous variation in climate, as well as provide a range of empirical evidence suggesting that climate shocks alter suicide rates, at least in part, via economic channels. The magnitudes of climate impacts on agricultural yield values and suicides are both economically and socially significant. Annual suicides per 100,000 people increase by 10.1%/σ, and annual yields fall by 1%/σ, for an increase in daily temperature within the 10-20°C range. Growing season precipitation increases annual yields by 0.9%/σ, but has no identifiable impact on suicide rates. We use seasonal “fingerprinting” and yield pattern matching to show that temperature impacts suicides and yields similarly, suggesting the presence of economic motives for suicide. For both temperature and precipitation, we employ a variety of heterogeneity tests and temporal disaggregation to establish further correlational evidence that agricultural losses motivate suicide in India.

However, our approach has important limitations. Primarily, we face the same challenge confronted in the climate and violence literature: without the ability to shut down the economic channel through which climate affects suicides, we cannot concretely identify the relevance of this mechanism. Although an instrumental variables methodology would likely be inappropriate due to a failure of the exclusion restriction, another option would be to include yields and climate jointly in a regression. However,
our agricultural and suicide data do not sufficiently overlap spatially or temporally to enable us to use this strategy.\footnote{Using the states and years for which both yield and suicide data are available leads to a sample size of 273. Results from regressions of suicide on climate variation controlling for yield are available upon request, but all climate variables are statistically insignificant, likely due to the small sample.} Secondly, the low spatial resolution of our suicide data limits the statistical power of our model and precludes us from exploring more detailed levels of heterogeneity, such as the impact of annual variation in irrigation or the differential responses in rural and urban areas. Perhaps due to this limited sample size, some of our results are not robust to the inclusion of regional time trends. Finally, although our temperature results clearly demonstrate a pattern match between agricultural yields and suicides, our rainfall findings are less clear. Due to extensive public discussion on growing season drought and suicide in India, our results suggest that further exploration of rainfall’s impacts on welfare is needed.

Despite these shortcomings, our results have important policy implications. Individual states in India, as well as the national government, have debated, enacted and sometimes repealed legislation seeking to prevent suicides by providing transfers or debt relief to subsistence farmers. Our results suggest that these policies could be effective, particularly in years of agriculturally damaging climate shocks. Moreover, our findings on the large magnitude of climate impacts on suicide is important for climate change policy design. Given the predicted increase in both temperature and rainfall for India over the coming century (Stocker et al., 2014), our results suggest a climate-driven rise in suicide rates in coming years for a country already battling a growing number of lost lives each year.

References


Blakeslee, David and Ram Fishman. 2013. “Rainfall shocks and property crimes in agrarian societies: Evidence from India.” Available at SSRN 2208292 .


8 Figures

Figure 1: Suicide rates over time

Notes: Suicide rates are measured annually per 100,000 people. Suicide count data are from India’s National Crime Records Bureau; population data are from the decadal Indian Census, linearly interpolated between census years. The full sample mean suicide rate is 9.47.
Figure 2: Lagged effects of climate on suicide

Notes: This figure shows coefficients for the impact of climate variables on suicide rates, estimated from Equation 3 using a degree day cutoff of 15°C and including two lags on all climate variables. Only coefficients for the first order of the precipitation polynomial only are shown.
95% confidence intervals for FE model. Mean annual suicide rate is 9.47 per 100,000.

95% confidence intervals for FE model. Mean log annual yield is 3.93.

Figure 3: Pattern matching of piecewise linear temperature response functions

Notes: Figure plots response functions using temperature bins of width 10°C from (a) a suicide regression with annual data for 32 Indian states between 1967 and 2013, and (b) an agricultural regression with annual data for 271 Indian districts between 1956 and 2000. Growing season is June-September, non-growing season contains all other months. Regional time trends use regions defined by [Nagara 2008] for suicide and [Guiteras 2009] for agriculture. Standard errors are clustered at the state level.
Figure 4: Distribution of cumulative degree days above 20°C in the growing and non-growing seasons

Notes: This figure shows the distribution of daily degree days above 20°C for the growing and non-growing seasons, using daily mean temperature for 32 of India’s states between 1967-2013. The growing season is June through September, while the non-growing season is all other months.

Figure 5: Geographic heterogeneity in the suicide-temperature response

Notes: Marginal effects are for the growing season only, and expressed as the percentage of the average coefficient across all states. They are estimated using a degree day model with a cutoff of 15°C. Darker states correspond to larger coefficients; yellow indicates a negative effect.
Figure 6: Correlations between agricultural variables and state-level suicide responses to temperature

Notes: Panel (a) shows the correlation between state-level suicide responses to growing season temperature and the average farmer suicide ratio, defined as farm suicides divided by total suicides. Panel (b) shows the correlation between state-level suicide responses and yield responses to growing season temperature, where only 13 states are included due to limited agricultural data. Temperature effects are expressed as each state’s proportion of the average treatment, where temperature is measured as growing season degree days above 15°C. Note that Kerala and Chhattisgarh are not states included in the agriculture data and therefore are not plotted in Panel (b).

Figure 7: Potential drivers of vulnerability to temperature

Notes: These figures plot the marginal effect of temperature on suicide for each of 32 Indian states, relative to (a) long-run average temperature and (b) long-run average suicide rates. Annual suicide data cover 1967-2013 and marginal effects are calculated using a degree days specification with a cutoff of 15°C.
(a) Suicide-precipitation response

95% confidence interval. Dashed line shows linear model. Mean annual suicide rate is 11.4 per 100,000.

(b) Yield-precipitation response

95% confidence interval. Dashed line shows linear model. Mean log annual yield is 3.93

Figure 8: Pattern matching of nonlinear precipitation response functions

Notes: Figure plots response functions using third degree polynomials in precipitation from (a) a suicide regression with annual data for 32 Indian states between 1967 and 2013, and (b) an agricultural regression with annual data for 271 Indian districts between 1956 and 2000. Growing season is June-September, non-growing season contains all other months. Regional time trends use regions defined by Nagaraj (2008) for suicide and Guiteras (2009) for agriculture. Standard errors are clustered at the state level.
Figure 9: Heterogeneity of suicide-precipitation response by irrigated area

Notes: This figure plots response functions from a regression using annual data for 32 Indian states between 1967 and 2013, where all precipitation variables are interacted with an indicator for being an “irrigated” state. A state is considered irrigated if its share of cultivated area under irrigation exceeded 50% for any year in my study sample (1967-2013), using data from the Indian Ministry of Agriculture.

Figure 10: Suicide-precipitation response by month

Notes: This figure plots the coefficients from a regression of annual suicide rates on cumulative millimeters of rainfall in individual months using data from 32 of India’s states between 1967-2013. Marginal effects were calculated controlling for a piecewise linear function of temperature in four 10°C bins, state and year fixed effects, and region-specific time trends with errors clustered at the state level. The growing season months are shaded in pink, harvest months shaded in green.
## Tables

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<th>Max.</th>
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Table 1: Summary statistics

*Note: Suicide data are from India’s National Crime Records Bureau and are reported annually at the state level. Yield data are from Duflo and Pande (2007) and are reported annually at the district level, valued in constant Rupees. Growing season is June-September, non-growing season contains all other months. Precipitation is measured cumulatively.*
## Table 2: Climate’s impact on suicide

Notes: Regression includes annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, non-growing season contains all other months. Regional time trends use regions defined by Nagaraj (2008) and described in the text. Standard errors are clustered at the state level.
## Table 3: Piecewise linear model for value of log yield (Rupees per hectare)

Notes: Regression includes annual data for 13 Indian states between 1956 and 2000. Growing season is June-September, non-growing season contains all other months. Regional time trends use regions defined by Guiteras (2009). Standard errors are clustered at the state level.
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Robust standard errors in parentheses

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

Table 4: 15°C degree day model of climate’s impact on suicide

Notes: Regression includes annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, non-growing season contains all other months. Degree day cutoff is 15°C. Regional time trends use regions defined by Nagaraj (2008) and described in the text. Standard errors are clustered at the state level.
### Table 5: Climate’s impact on suicide: indicators for drought and surplus

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<td>0.908</td>
<td>0.916</td>
</tr>
<tr>
<td>State FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year FE</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Region × Year Trend</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>

Standard errors clustered at the state level

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

**Notes:** Regression includes annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, non-growing season contains all other months. Drought is defined as an indicator equal to one when annual rainfall is in the 20th percentile or below, while surplus is equal to one when annual rainfall is above the 80th percentile. Standard errors are clustered at the state level.