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Male backlash, bargaining, or exposure reduction?: women's working status and physical spousal violence in India

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Abstract Labor force participation of women is expected to decrease the risk of spousal violence by enhancing their bargaining power or diminishing their contacts with abusive partners. The opposite effect is predicted when female employment induces male backlash. I identify the effect of female employment on spousal violence by exploiting the exogenous variations in rural women's working status driven by rainfall shocks and the rice–wheat dichotomy. The instrumental variable regression result indicates that female employment significantly reduces the incidence of spousal violence. This result is mainly driven by the exposure reduction effect that dominates male backlash. There is, however, no evidence on the bargaining effect.

Keywords Violence · Female employment · Exposure reduction

JEL Classification J12 · J16 · J43

1 Introduction

Empowerment of women is not only an important goal of development in itself but also an effective policy tool for promoting economic growth and development. Improved education, better labor market outcomes, and more financial resources for women are expected to generate outcomes such as favorable intra-household allocations, poverty reduction, and improved human capital

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for the next generation (Behrman et al. 1999; Duflo 2003; Pitt and Khandker 1998; Senauer et al. 1988; Rosenzweig and Schultz 1982; Qian 2008).

Policies that promote gender equality implicitly assume that women with better social or economic standing can exercise higher bargaining power within the household and achieve allocations advantageous to themselves and children. However, it is questionable whether the improved status of females always enhances their bargaining power. Given that bargaining power materializes through better options outside of marriage, in a patriarchal culture where divorce is not an option for women, better social or economic status of females may not necessarily translate into higher bargaining power. Instead, it might challenge the socially prescribed dominance of men and trigger male backlash (Aizer 2010; Luke and Munshi 2011).

Patterns of spousal violence in India suggest the possibility of male backlash in the sense that women who participate in the labor market are more likely to be subject to physical violence than non-working women are. Given that women in India virtually do not have options outside of marriage, India might be a suitable arena for male backlash or extraction to exist.

However, the interpretation of the empirical finding is made difficult by issues of endogeneity. For instance, the positive correlation between physical violence and women's employment status may reflect the causal effect of domestic violence on the decision to work rather than the effect of work status on domestic violence. Further, the positive effect might be driven by omitted variables. For example, poor women tend to work more than women in rich households do. At the same time, they are subject to greater violence than their counterparts. Thus, if poverty is omitted, the effect of female employment on violence would be confounded with the effect of poverty.

In this paper, I identify the effect of female labor force participation on the incidence of spousal violence in India. Further, I explore the underlying mechanisms through which female employment affects the risk of spousal violence.

The main contributions of this study are twofold. First, I identify the effect of female employment on spousal violence by using the plausibly exogenous variations in rural women's labor market outcomes. The identification strategy exploits the rice–wheat dichotomy, a unique regional variation in crop production in India, interacted with rainfall shocks. The idea is that rainfall shocks generate a regional variation in demand for female labor, depending on the choice of crop, which leads to an exogenous change in female labor force participation. The instrumental variable regression result indicates that labor force participation of women decreases the probability of physical spousal violence.

Second, I find that the negative effect of female employment is mainly driven by a strong exposure reduction, a finding that has not been verified by other studies. The exposure reduction suggests that when the time spent outside of the home increases, a woman is less exposed to a potential abuser within the home, which leads to a decrease in abuse (Dugan et al. 1999, 2003). The existing spousal violence studies in developing countries often identify

backlash or extraction effects of financial resources in the hands of women (Bloch and Rao 2002; Luke and Munshi 2011; Koenig et al. 2003). A backlash effect occurs when a husband commits spousal violence as a way of expressing his antipathy toward female independence, whereas an extraction effect occurs when a husband uses spousal violence as an instrument to extract a financial transfer from his wife.

On the other hand, there has not been a study that explores the exposure reduction effect of female employment in a developing country context.[1] In this study, while I find some suggestive evidence on the backlash or extraction effects of female employment, those effects are found to be dominated by the exposure reduction effect. In addition, I find no convincing evidence on the bargaining effect of female employment.

Culture can be a binding constraint in implementation of an economic policy. Policies implemented without consideration of underlying culture has a risk of entailing undesirable outcomes. The significance of the current study lies in that it provides useful guidance for polices that center on women and gender inequality, by analyzing how economic factors interact with cultural factors.

The paper proceeds as follows. Section 2 discusses the existing literature on spousal violence and its limitations; Section 3 describes datasets used in this study; Section 4 explains the empirical strategy; Section 5 reports the results, and Section 6 provides a conclusion.

2 Background

Existing economic research on spousal violence is largely based on marital bargaining models. These models predict that an increase in women's economic opportunities, relative to men's, will allow favorable outside options for women and lower their threshold for tolerating abuse within marriage, thereby reducing the incidence of violence (Farmer and Tiefenthaler 1996, 1997; Lundberg and Pollak 1994; Tauchen et al. 1991). Numerous empirical studies find that a better economic status of women, represented by higher income, more employment, or larger dowries, reduces marital violence (Aizer 2010; Farmer and Tiefenthaler 1997; Srinivasan and Bedi 2007; Tauchen et al. 1991).

On the other hand, the exposure reduction theory in criminology suggests that conditions that contribute to shortening the time that a woman in a violent relationship is in contact with the abusive partner decrease the risk of violence (Dugan et al. 1999, 2003). Thus, the exposure reduction effect may occur, to the extent that increased economic opportunities for the woman would decrease the time that the couple spends together. However, the exposure

[1] Aizer (2010) investigates the exposure reduction effect of a favorable labor market condition for women, but her study uses data in the United States.

reduction effect of female employment has little empirical support. Aizer (2010) investigates the effect of gender wage gap on violence using data in the United States. She finds that marital violence declines, when there is a favorable market condition for women. The decline is greater, however, on weekends than on weekdays, which is not consistent with the exposure reduction theory.

In contrast, models that focus on the symbolic nature of the economic status of women suggest the opposite effect. When the improved status of women challenges socially prescribed male dominance and female dependence, women may be subject to more spousal violence, as the challenged man might try to reinstate his authority over his wife by inflicting violence on her (Hornung et al. 1981; Macmillan and Gartner 1999; Molm 1989). Models that predict such a backlash effect can be criticized because they ignore women's rationality constraint, the possibility of ending the relationship (Aizer 2010). However, in cultural surroundings where divorce or separation is accompanied by significant stigma, the threat of ending the relationship by women may not be credible (Luke and Munshi 2011; Srinivasan and Bedi 2007). Empirical studies conducted in some culturally conservative areas find that greater financial independence of women, measured by income or membership in credit groups, elevates the risk of violence (Luke and Munshi 2011; Koenig et al. 2003).

A similar but slightly different mechanism suggests that a husband may exercise greater violence on a woman with more financial resources, in order to extract a monetary transfer from her (Bloch and Rao 2002; Goetz and Gupta 1996).[2] Empirical evidence on the extraction effect is provided by Bloch and Rao (2002) in their study of three villages in India. They find that the risk of spousal violence is higher for a woman from a rich household, which confirms the extraction motive of the husband.

In addition, it is possible that working women report violence at a higher rate than non-working women do, because they learn that violence should not be tolerated through frequent contacts with people outside the home. This higher reporting of violence as a labor market outcome has not been explored in previous literature but will be addressed in this study.

The previous empirical studies generally suffer from endogeneity bias.[3] The economic status of women, measured by employment status (Farmer and Tiefenthaler 1997; Macmillan and Gartner 1999), income (Bloch and Rao 2002;

[2]Although the two explanations—backlash and extraction—predict the same positive effect, the extraction effect is intrinsically different from the backlash effect. The backlash effect characterizes violence as expressive, whereas the extraction effect defines violence as instrumental. In this study, however, it is not possible to differentiate between the two effects.

[3]A few exceptions are the studies by Aizer (2010) and Luke and Munshi (2011). Aizer (2010) measures an exogenous change in female economic status by the ratio of wages in female dominated industries to wages in male dominated industries. Luke and Munshi (2011) instrument female and household income with land elevation and rainfall shocks. The main difference between their studies and the current study is that, while their studies identify the bargaining or backlash effects of female status, this study provides evidence on the exposure reduction effect.

Farmer and Tiefenthaler 1997; Tauchen et al. 1991), education level (Hornung et al. 1981), dowry (Srinivasan and Bedi 2007), or participation in credit programs (Koenig et al. 2003) is typically endogenous, given that they are the choices made by a woman or the household. There might be unobservables that are correlated with both the economic status of a woman and her spousal violence experience. Also, a woman's economic status might be a result of spousal violence rather than the cause of the violence. These shortcomings limit the interpretation of the results. Furthermore, some of these studies use non-random samples, such as victims of violence who choose to seek outside help (Farmer and Tiefenthaler 1997; Tauchen et al. 1991). This, again, limits generalization of the results. In this study, I overcome the shortcomings of previous literature by exploiting the exogenous variations in a labor market outcome of women, using nationally representative random samples.

3 Data

The main data used in this study come from the second National Family Health Survey (NFHS-2) of India 1998–1999. The survey covers a representative sample of 90,303 eligible women aged 15–49 from 26 states that comprise more than 99% of India's population. The survey provides data on a variety of demographic and health issues including domestic violence, such as ever-experience of women's domestic violence since age 15, persons who inflicted ever-violence, and the frequency of violence in the past 12 months.

Based on the information provided, I construct a dummy for experiencing violence committed by husbands in the past 12 months, which is the key dependent variable in this study. In doing so, I drop the women who ever-experienced violence committed not only by husbands but also by other persons. The dataset provides the information on the inflictor of ever-violence, but not the inflictor of the past year's violence. Therefore, when a woman affirms the experience of violence in the past 12 months, we cannot tell whether it was spousal violence or not. Dropping those women who also experienced violence committed by persons other than their husbands reduces the sample size to 85,965.

Further, the eligible women report whether they worked in the past 12 months. Using this information, I construct a dummy for female employment in the past 12 months, which is the key independent variable in this study. Interestingly, there is a positive association between the two variables. While 11%of women who worked in the past 12 months report the experience of spousal violence in the past year, the corresponding figure for non-working women is 7% (Table 7 in Appendix 1). This positive association might reflect the backlash or extraction motives of men against female independence in a patriarchal society. At the same time, the positive association might be driven by reverse causality or omitted variable bias, as discussed in Section 1. Therefore, it is necessary to establish a convincing identification strategy to

determine the causal relationship between the working status of females and spousal violence.

The identification strategy of this study, which will be discussed in greater detail in Section 4, exploits regional differences in the effect of rainfall shocks on the rural labor demand. Thus, I restrict the main sample of this study to rural households, which reduces the sample size to 59,253. I further restrict the sample to landless households, so that the instrument for female employment operates through the employment status only, and not through agricultural profits. This, again, reduces the sample size to 19,953.

The additional determinants of spousal violence other than the female employment status include variables such as age, education, and household size, as well as state level covariates.[4] Dropping some of the samples with missing data on these covariates further reduces the sample size, so that the final sample is then 19,074 households over 18 different states.

Further, the 18 different states are divided into two sub-areas: the rice-growing area and the wheat-growing area, based on which crop is dominant in each state. This division of data is, again, related to the identification strategy that exploits regional differences in the effect of rainfall shocks on the rural labor demand. For crop information, I use the Indian District Database 1961–1991 (Vanneman and Barnes 2000), which provides data on different crop areas in 1981 across 366 districts. I aggregate district level rice areas and wheat areas to state level and determine which states belong to the rice- or wheat-growing region.[5] The rice-growing area includes Andhra Pradesh, Assam, Bihar, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Orissa, Tamil Nadu, and West Bengal. The wheat area includes Gujarat, Haryana, Himachal Pradesh, Punjab, Rajasthan, and Uttar Pradesh.

On the other hand, rainfall information comes from the high resolution gridded daily rainfall data by the India Meteorological Department (India Meteorological Department 2005). The dataset contains interpolated rainfall information for a series of $1 \times 1^\circ$ grids covering India. I compute the state level rainfall by averaging all of the gridded rainfall data that apply to one state. Then, the rainfall shocks at each state are defined by the difference of the yearly rainfall from the normal rainfall (30-year average). There are several other datasets used in the study for robustness checks.[6] A brief explanation of the auxiliary data is provided in Appendix 2.

Table 1 reports the descriptive statistics of spousal violence, female employment, and other control variables of the main sample. Overall, 13% of the women in rural landless households experience spousal violence in the

[4]The list and definitions of the variables are provided in the notes below Table 1.

[5]If the rice–wheat ratio, which is defined by a rice area/(rice area + wheat area), in a state is greater than 0.5, it is defined as a rice state.

[6]The datasets include the Rural Economic and Demographic Survey 1998–1999 by the National Council of Applied Economic Research, Districtwise Area and Production of Principal Crops in India by Directorate of Economics and Statistics, and a rain-gauge-based 0.5° daily grid precipitation product by the APHRODITE project.

Table 1 Summary statistics of variables

	NFHS-2 agricultural landless		
	All	Rice	Wheat
Violence in the past year	0.130 (0.329)	0.137 (0.344)	0.104 (0.284)
Work in the past year	0.420 (0.488)	0.461 (0.497)	0.275 (0.435)
Woman age	29.840 (8.912)	29.883 (8.951)	29.687 (8.813)
Man age	36.335 (10.198)	36.822 (10.258)	34.613 (9.908)
Number of children	2.571 (1.839)	2.481 (1.808)	2.889 (1.901)
Woman education	2.285 (3.684)	2.447 (3.739)	1.713 (3.514)
Man education	4.223 (4.443)	4.081 (4.36)	4.725 (4.61)
Number of women	3.043 (1.871)	2.978 (1.881)	3.272 (1.841)
Number of men	3.226 (1.963)	3.099 (1.9)	3.676 (2.081)
Low caste	0.713 (0.448)	0.713 (0.448)	0.712 (0.446)
Wealth	−0.513 (0.719)	−0.564 (0.666)	−0.331 (0.774)
Rice major state × shock	111.969 (178.510)		
Rainfall shock	142.537 (188.198)	143.621 (205.6)	138.703 (116.03)
Rice major state	0.780 (0.449)		
Total crop area (per capita)	0.282 (0.129)	0.256 (0.115)	0.372 (0.098)
Total crop area (per capita) × shock	35.555 (56.215)	29.832 (46.865)	55.802 (60.177)
Arable land (per capita)	0.019 (0.582)	0.005 (0.075)	0.071 (1.095)
Distance	0.043 (0.434)	0.05 (0.496)	0.017 (0.194)
No. of observation	19,074	13,751	5,323

All observations are weighted by probability weights. Standard deviations in parenthesis. Violence in the past year: a dummy that takes 1 if there was an incidence of violence in the past year, work in the past year: a dummy that takes 1 if a woman worked in the past year, number of children: the number of children within the household, woman education: highest grade completed by the wife, man education: highest grade completed by the husband, number of men: the number of men within the household, number of women: the number of women within the household, low caste: a dummy that takes 1 if the household head is scheduled caste or scheduled tribe, wealth: an index constructed using household asset data and principal components analysis, rice major state: a dummy that takes 1 if the household resides in a rice state, rainfall shock: difference of the yearly rainfall from the normal rainfall (30-year average) at the state level, measured in millimeters, total crop area (per capita): size of the per capita crop area for 33 major crops in a state, measured in hectares, arable land: the size of arable land in a village, measured in 1,000 ha, distance: the distance to the nearest town in a village, measured in 1,000 km

past 12 months. Their labor force participation rate is as high as 42%. The social standing of the sample households is low in that 70% of the sample belongs to a low caste. Couples have from two to three children, and the men are older and more educated than the women. While there is no remarkable difference between the two crop areas in other demographic characteristics, the fact stands out that a higher proportion of women in the rice-growing area experience spousal violence than do their counterparts in the wheat-growing area (14% vs. 10%). Further, a higher proportion of women residing in the rice-growing area participate in the labor force than women in the wheat-growing area (46% vs. 28%). While these regional differences resemble the correlation between female employment and spousal violence discussed above, the causation of the relationship has yet to be determined. I address the identification strategy in the next section.

4 Empirical analysis

4.1 Regression equations

The primary interest of this study is focused on how female employment affects spousal violence towards her. Therefore, the main regression equation is defined by:

$$V_{is} = \alpha_0 + \alpha_1 W_{is} + \beta X_{is} + \tau Z_s + \varepsilon_{is}, \quad (1)$$

where V_{is} is a dummy for violence experience of a woman in household i in state s in the past 12 months, W_{is} is a dummy for the working status of the woman in the past 12 months. Further, X_{is} includes household level covariates,[7] and Z_s covers state level covariates, including rainfall shocks (S) and the rice state dummy (r).[8] As explained earlier, rainfall shocks (r) are defined by the difference of the yearly rainfall from the normal rainfall (30-year average) at the state level, measured in millimeters. Lastly, ε_{is} is unobservables.

The female working status (W_{is}) is endogenous to the violence experience of women (V_{is}), rendering a causal interpretation of α_1 difficult. I address this problem by using the method of instrumental variable.

The first stage equation is defined by:

$$W_{is} = \phi_0 + \phi_1 \left[S \times r\right]_s + \pi X_{is} + \kappa Z_s + \upsilon_{is}, \quad (2)$$

where $[S \times r]_s$ is the instrument, the interaction between rainfall shocks (S) and the rice state dummy (r) in state s. The coefficient ϕ_1 captures how the instrument affects the probability of female employment. Further, υ_{is} is a disturbance term. A detailed discussion on the instrument will be provided in the next section.

[7] Household level covariates cover variables such as woman age, man age, number of children, woman education, man education, number of men in the household, number of women in the household, a low-caste dummy, and wealth index. The wealth index is constructed using household asset data and principal components analysis. Assets include a number of consumer items such as a telephone, bicycle or car as well as availability of drinking water and sanitation facilities, etc. Each asset is assigned a score generated through principal components analysis and the scores are summed by each household (Kishor and Johnson 2004).

[8] Additional state level covariates are crop variables such as total crop area per capita in hectares, total crop area per capita interacted with rainfall shocks. Also included are some village level variables such as arable land per capita in 1,000 ha and the distance from the nearest town in 1,000 km.

In addition, the reduced form equation, which measures the direct effect of the instrument on the probability of spousal violence, is defined by:

$$V_{is} = \zeta_0 + \zeta_1 \left[S \times r\right]_s + \vartheta X_{is} + \psi Z_s + \xi_{is}, \quad (3)$$

where ξ_{is} is a disturbance term and all other variables are as defined above. The coefficient ζ_1 captures the effect of the interaction term ($[S \times r]_s$) on spousal violence (V_{is}) through the working status of females (W_{is}).

4.2 Instrument

The rice–wheat dichotomy in female employment and rainfall shocks are joint determinants of female labor force participation. In India, the female labor force participation rates are consistently higher in the rice-growing eastern and southern states than in the traditional wheat-growing belt of the northwest. This geographically distinct employment variation is related to differences in farming patterns between the two crops: in the rice-growing region, where women have a comparative advantage in weeding and transplanting, demand for female labor is high, whereas in the wheat-growing region, where plough cultivation is prevalent, demand for female labor is low. (Bardhan 1974; Boserup 1970; Indian National Science Academy and Chinese Academy of Sciences 2001; Miller 1981). Figure 1 presents employment rates by gender

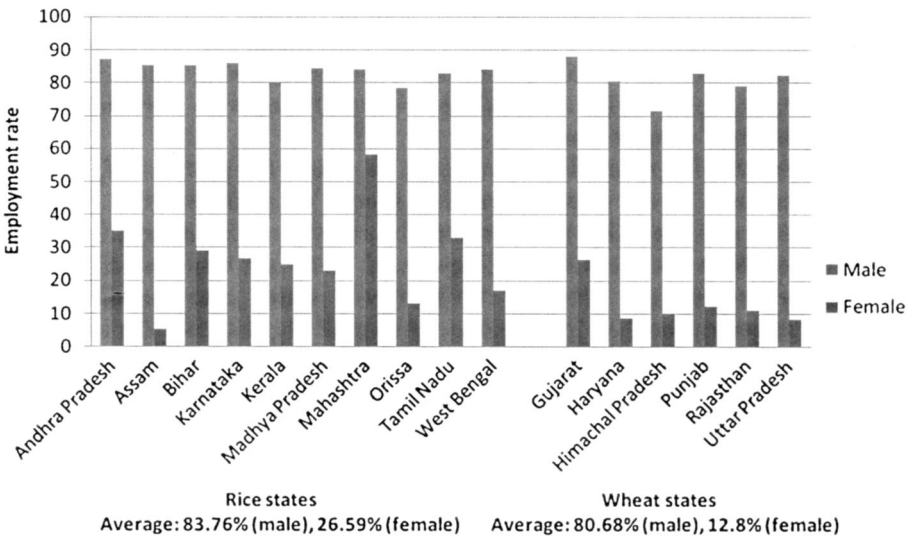

Fig. 1 Male/female employment rate by state. *Source*: REDS 1998-1999. *Notes*: The employment rates are calculated by the author based on the primary activity status of each household member in the survey. Among the 18 states covered in this paper, Manipur and Meghalaya are not included due to lack of observations

in rice and wheat states using the Rural Economic and Demographic Survey (REDS) 1998–1999. While no stark difference in male employment rates exists between the two regions, female employment rates are considerably higher than 20% in most of the rice states, while the rates are around 10% in most of the wheat states.

Further, rainfall shocks can serve as the second dimension of variation in female employment. Crop productions in India are generally dependent upon rainfall, and positive rainfall shocks are known to be associated with an improved demand for female labor in wet agriculture (Luke and Munshi 2011; Rosenzweig 1990; Rosenzweig and Schultz 1982).More importantly, rice production requires far more water than wheat production (Mbiti 2008). Positive rainfall shocks, then, would increase the demand for female labor in rice-growing regions more than they would in wheat-growing regions, yielding a systematic regional difference in female labor force participation. Therefore, I suggest the interaction between rainfall shocks and a dummy for being in a rice state ($[S \times r]_s$) as an instrument for female labor force participation (W_{is}). In doing so, the identification assumption is that the interaction term is uncorrelated with unobservable violence propensities and is excluded from the main regression equation (Eq. 1).

Column 3 of Table 2 reports the estimate of ϕ_1 in the first stage equation (Eq. 2), using the main sample of this study. The result indicates that the interaction term is associated with an improved probability of female employment. More specifically, one additional millimeter of rainfall shocks in the rice-growing region increases the likelihood of female employment by 0.002. Further, column 4 reports the estimate of ζ_1 in Eq. 3, the reduced form effect of the interaction term on the likelihood of violence (V_{is}). The estimate is negative and significant at the 10% level. Combining the two results, the interpretation is that more rainfall shocks in the rice-growing region improve female employment in the area, which eventually leads to a reduction in violence directed towards women.

However, this interpretation should not be taken for granted. If, for example, there is a direct effect of rainfall shocks on unobservable violence propensities,[9] and the effect is differential by crop state, the interaction term is correlated with unobservables. Likewise, if there is a regional difference in violence propensities between the two crop states, and the difference becomes larger or smaller in response to rainfall shocks, the identification assumption is violated. In other words, the identification strategy fails, if the instrument affects violence through other channels than female labor force participation.

[9]For example, studies in meteorology suggest that, other things being equal, rainfall decreases violence rates though cooling down effects (Simister and Van de Vliert 2005; Van de Vliert et al. 1999).

Table 2 Reduced form and first stage estimation results

Group	NFHS-2 urban large cities		NFHS-2 agricultural landless		REDS		
Dependent variable	Work (1)	Violence (2)	Work (3)	Violence (4)	HH labor income (5)	Male work day (6)	Female work day (7)
Controls							
Rice major state × shock	0.0002458	−0.0000455	0.0019522	−0.0001384	6.557009	−0.0116311	0.4013401
	(0.000195)	(0.0001639)	(0.0004755)***	(0.00007325)*	(20.252163)	(0.1522771)	(0.1251903)**
No. of observation	6,570	6,570	19,074	19,074	606	1,747	267
R^2	0.0577	0.0487	0.1954	0.0317	0.2519	0.1314	0.1515

Robust standard errors are in parenthesis

***Significant at 1%

**Significant at 5%

*Significant at 10%

I explore such a possibility by conducting a control experiment using a sample of households that reside in capitals or large cities. The idea is that rainfall shocks do not have differential effects on female employment by crop state in this control area, because most of the available jobs in capitals or large cities are in the non-agricultural sector.[10] Therefore, the instrument would have an insignificant effect on the working status of women (W_{is}) in this control group. Given that it does not change the working status of women in this group, the interaction term would not affect the violence experience of these women (V_{is}), either. In contrast, if the interaction term has a significant effect on the probability of spousal violence, while it is insignificant for female employment, then such a result would suggest that the interaction term operates through channels other than female labor force participation, thereby violating the identification assumption.

In Table 2, column 1 reports the first stage effect (ϕ_1), and column 2 reports the reduced form effect (ζ_1) of the interaction term in the control experiment. The instrument has an insignificant effect on the working status of women and, accordingly, an insignificant effect on spousal violence. This result suggests that female labor force participation is plausibly the exclusive channel. Given that the reduced form effect in the control group (column 2) is largely insignificant (p value 0.785), we cannot reject the hypothesis that the reduced form effect in the control group is insignificantly different from the effect in the treatment group (column 4). Nevertheless, these results are still encouraging in that they provide some suggestive evidence in support of the identification assumption.

5 Results

5.1 Baseline results

Table 3 reports the basic OLS and the instrumental variable estimates of the effect of female working status (W_{is}) on women's violence experience (V_{is}).

Naïve OLS regression result among rural landless households is reported in column 3. The result indicates that, when a woman works, the probability of physical spousal violence increases by 0.033. However, when the female working status is instrumented by the interaction between the rice–wheat dichotomy and rainfall shocks, an exogenous change in female employment decreases the probability of physical spousal violence by 0.07 at the 10% significance level (column 4). Therefore, the instrumental variable estimate supports the violence reduction effect of female employment. It further suggests that the positive effect of women's working status on spousal violence in

[10] In the data, only 0.42% of working women in capitals and large cities are engaged in the agricultural sector.

Table 3 Basic OLS and IV estimates of the effect of female employment

Group	NFHS-2 urban large cities		NFHS-2 agricultural landless (All)		NFHS-2 agricultural landless (Four states)	
Method	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Controls						
Female employment	0.0227	−0.1850	0.0332	−0.0709	0.0180	−0.3491
	(0.0112)*	(0.6110)	(0.0088)***	(0.0417)*	(0.0181)	(0.0505)***
No. of observation	6,570		19,074		3,915	

Robust standard errors are in parenthesis

***Significant at 1%

*Significant at 10%

the naïve OLS regression is due to endogeneity of the working decisions by females.

Similarly, female employment has a positive effect on the risk of violence among households in urban areas at the 10% level (column 1). The instrument variable estimation, however, yields an insignificant effect of female employment on violence in this control group. This falsification test result, using females whose working status is invariant to the proposed instrument, again supports the validity of the identification strategy.

5.2 Robustness check

While the falsification test result using urban households in Section 5.1 is encouraging, concerns still remain about the identification assumptions of the analysis based on rural households: first, the instrument might be correlated with male employment or household labor income, both of which are missing variables in the main dataset;[11] second, the instrument might yield a differential proximity effect across regions, if there is a considerable difference in house size between the two crop states; third, the instrument might have a differential impact on agents' utility associated with crop consumption.

(1) Male employment and household income: apart from female employment, rainfall shocks might also have a differential impact on male employment or household labor income by crop state. Since the two variables are missing in the main dataset, this is potentially a threat to the exclusion restriction.[12]

In order to determine whether this is a valid concern, I use REDS 1998–1999, which provides information on work days of household members and household labor income in rural India. I first investigate whether both male and female work days are significantly affected by the interaction term, by regressing male work days or female work days on independent variables defined in Eq. 2. Table 2 columns 6 and 7 report the results. The interaction term has a significant positive effect on female work days (column 7). This suggests that rainfall shocks in the rice-growing area have a stronger positive effect on female work days than rainfall shocks in the wheat area. This is

[11] Unfortunately, NFHS-2 does not provide data on male working status or household income. It does contain information on husbands' usual occupations—answers to the question "What kind of work does (did) your (last) husband mainly do?"—But this information does not necessarily translate into the husbands' working status during the past 12 months.

[12] The falsification test using households in capitals or large cities, unfortunately, does not directly disprove this concern. It is because male employment or household labor income in the non-agricultural economy are not expected to be affected by the instrument. Therefore, omitting the two variables would not serve as a potential source of bias in the control experiment, whereas it might do so in the main sample based on agricultural households.

consistent with the first stage regression result on female employment shown in column 3. On the other hand, for men, the interaction term has no significant effect, which suggests that the effect of rainfall shocks on male work days does not differ by crop state (column 6).[13] Although the analysis uses work days, instead of the employment status, the implication is still that the interaction term is not correlated with labor market outcomes of males. Therefore, the result suggests that male employment is not a potential source of bias.

Further, I explore a possibility that the interaction term is correlated with household labor income, by regressing household labor income on the independent variables defined in Eq. 2. Column 5 of Table 2 shows that rainfall shocks do not generate a significant differential effect on household labor income by crop state. This suggests that omitting household labor income would not bias the effect of female employment.[14]

(2) Differential proximity effect: Excessive rainfall shocks might induce people to stay inside the house longer than usual. If house size in the wheat states is considerably smaller than that in the rice states, more rainfall shocks might expose women in the wheat states to a greater risk of violence through frequent contacts with abusive partners in a confined area. Then, this proximity effect might bias the female labor effect.

While house size cannot be directly controlled due to lack of data, I explore the concern by presenting the distribution of the per capita floor area for the two crop states. Figure 2 plots the number of households (out of a thousand) against the per capita floor area (in square meters) by crop state. The difference in the two distributions, if at all, suggests that the proximity effect may not be a major threat. While there is no remarkable difference in the distributions, the proportion of households that use a very small area is slightly higher in the rice-growing states than in the wheat-growing states. For example, 123.3 out of 1,000 households use 1–3 m^2 per capita in the rice area, whereas the corresponding figure is 94.76 in the wheat area. Accordingly, the cumulative distribution in Fig. 2 indicates that 72% of the households in the rice states live in a house with a per capita floor area smaller than 11 m^2, whereas the corresponding figure is 70% in the wheat states. This suggests that the proximity effect driven by rainfall shocks, if any, would be slightly greater in the rice area. Therefore, this potential bias does not work against

[13] A similar finding has been made by Rosenzweig and Schultz (1982). In their study, while female employment is positively correlated with district normal rainfall, the rainfall has an insignificant effect on male employment.

[14] If the income contribution of a woman is relatively low, a change in female working status or work days might not necessarily translate into a significant change in the household labor income. Therefore, a significant change in female working status, but an insignificant change in the household labor income driven by the instrument can be because the female income contribution is relatively low.

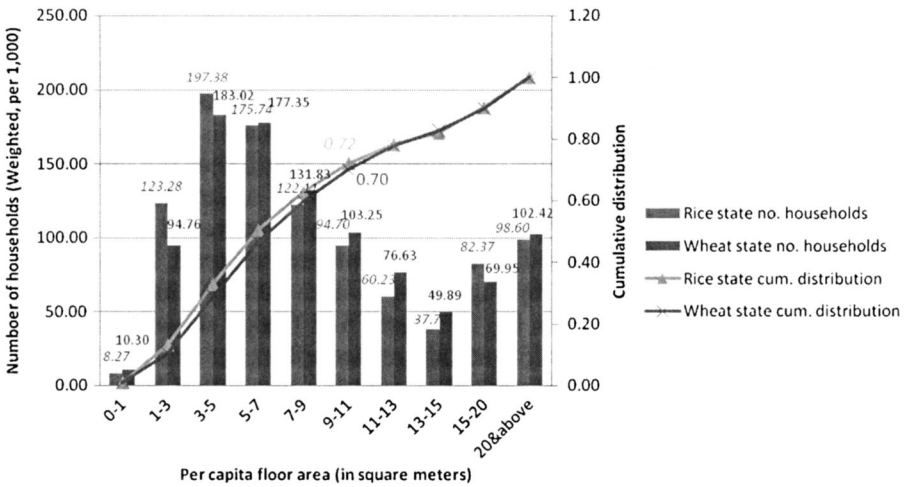

Fig. 2 Distribution of number of households by per capita floor area. *Source*: Housing Condition in India (1993), NSS report no. 429, National Sample Survey Organization, Government of India. *Notes*: The number of households in the rice (wheat) area is the weighted average of households in all of the rice (wheat) states. The weight is determined by the ratio of the number of households in a given state to the total number of households across all of the rice (wheat) states

the identification strategy, since such bias would result in underestimation (in absolute term) of the effect of female employment.

(3) Differential utility effect: If the rice-producing states are also disproportionately rice-eating states, rainfall shocks in the rice states might increase the happiness of forward-looking men who expect abundant rice at lower prices. Then, their improved happiness might lead to a reduction of violence.

I argue that this is not a potential source of bias based on two pieces of evidence. First, Fig. 3 presents that the average per capita rice consumption of the urban population is 7.72 kg in the rice-growing area, while it is 1.55 kg in the wheat-growing area. Given that there is a considerable regional difference in rice consumption among the urban population, if rainfall shocks induce a differential happiness-improving effect between the two crop states, the effect would be captured in the control experiment using urban households. However, as discussed in Section 4.2, the reduced form effect of the instrument on spousal violence using the control group is insignificant (column 2 of Table 2). In other words, rainfall shocks do not generate a differential happiness-improving effect by crop state. This suggests that the happiness-improving effect may not be a problem.

Second, I restrict the sample to households in Maharashtra, Karnataka, Gujarat, and Uttar Pradesh—two from the rice states and two from the wheat states—where the rice consumption levels range from 2.14 to 4.89 kg. Given that their rice consumption level is similarly low, a regional difference in the

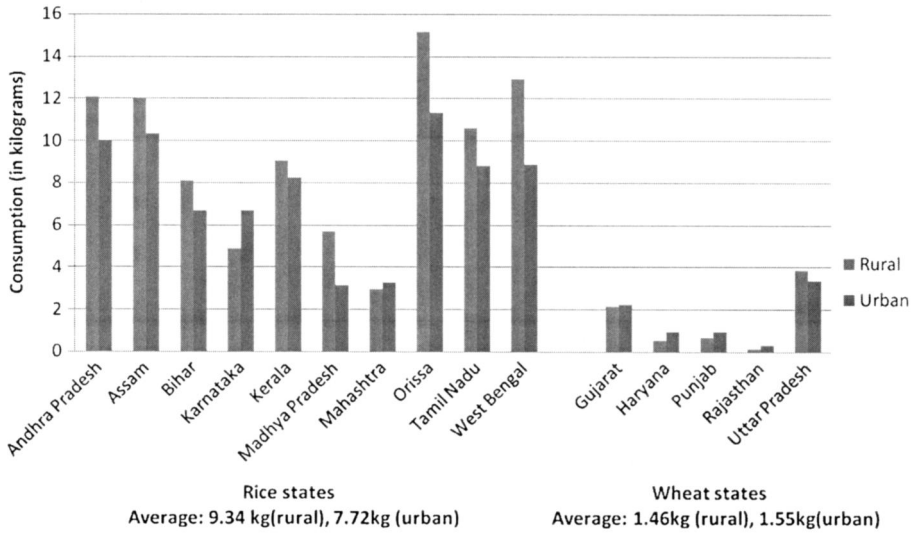

Fig. 3 Rural/urban rice consumption by state. *Source*: Household Consumer Expenditure and Employment Situation in India (1999), NSS report no. 448, National Sample Survey Organization, Government of India. *Notes*: Out of 18 states in the main sample, Manipur, Meghalaya, and Himachal Pradesh are not included due to lack of data

happiness-improving effect would be minimal in this restricted sample. If the significant negative effect of a female working in the main sample (−0.07, column 4 of Table 3) is indeed driven by the happiness-improving effect, the instrumental variable estimate of female employment using this restricted sample would provide a smaller or even a null effect. However, the result using the four states indicates that female employment decreases the probability of violence by 0.35 (column 6 of Table 3), suggesting that male preference may not be a threat to the exclusion restriction.

5.3 Heterogeneous effects

In order to examine the underlying mechanisms of how women's labor force participation affects their violence experience, I divide the sample into separate groups and compare the heterogeneous effects of female employment among the sub-groups. NFHS-2 reports the degree of the contribution of working women to the household income.[15] Based on this information, I define the sub-groups. A description and the expected effects of female employment in each sub-group are reported in Table 4.

[15]Women's contribution to the household income is a categorical variable that takes 1 if the contribution is almost none, 2 if it is less than half, 3 if it is about half, 4 if it is more than half, and 5 if it is all.

Table 4 Expected effects of female employment by sub-group

Effects	Negative		Positive	
	Bargaining	Exposure reduction	Backlash	Labor market outcome
Sub-group				
Group A. Working with compensation	O	O	O	O
Group B. Working with negligible compensation	X	O	X	O
Group C. Working with negligible compensation and husbands in non-agriculture	X	X	X	O

In group A, "working women" covers only those women whose earnings positively contribute to the household income. Since they earn financial resources through working, their employment would induce not only the bargaining effect, but also male backlash. In addition, work outside the home would entail exposure reduction, as well as a higher rate of violence-reporting as a labor market outcome.

On the other hand, in group B, "working women" covers only those females whose earnings contribute none or little to the household income. It is assumed that, if labor force participation of women does little to increase their financial resources, its bargaining effect, as well as men's incentives for backlash or extraction, would be minimal. Thus, female labor force participation in this group affects spousal violence through either the exposure reduction effect or the labor market outcome effect.

Further, in order to explore the labor market outcome effect more closely, I refine group B so that it covers only the women whose husbands are engaged in non-agricultural work (group C). The idea is that, if husbands are engaged in the non-agricultural sector,[16] where work schedules are relatively inflexible, the exposure reduction effect of female employment would be minimal. This is because husbands are away from home during the day anyway, and labor force participation of wives during the day does not change their exposure to abusive situations. The employment status of these women is, therefore, likely to capture only the labor market outcome effect. Table 5 reports OLS and the instrumental variable estimation results by sub-group.

Column 6 reports the instrumental variable estimate of the effect of female employment on spousal violence using group C. Given the rigid work schedules of the husbands, as well as the lack of compensation, work outside the home among these women is expected to have only the labor market outcome effect. The largely insignificant employment effect in column 6 (p value 0.379), however, suggests that female labor force participation does not result in a higher rate of violence-reporting.

[16]Non-agricultural occupations include professional jobs, technicians, management, clerical work, sales, and services.

Table 5 Heterogeneous effects of female employment by sub-group

Sub-group	Group A (Compensation)		Group B (Non-compensation)		Group C (Husband non-agriculture)	
Method	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Controls						
Female employment	0.0366	−0.0613	0.0154	−0.2464	−0.0036	0.2747
	(0.0080)***	(0.0383)	(0.0199)	(0.1243)**	(0.0188)	(0.3122)
No. of observation	18,528		13,071		2,894	

Robust standard errors are in parenthesis

***Significant at 1%

**Significant at 5%

Column 4 reports the instrumental variable estimate of the female labor effect on spousal violence using group B. It is assumed that the lack of financial resources in the hands of women in this group would rule out male backlash or extraction, as well as the bargaining effect. Therefore, assuming that the labor market outcome effect is non-existent based on the result in column 6, female employment would have an exposure reduction effect only. Column 4 reports that female employment reduces the probability of violence towards them by 0.25 and the effect is statistically significant. This suggests the presence of the exposure reduction effect.

On the other hand, column 2 reports the effect of female employment in group A, for which all four effects are assumed to be present. While the magnitude of the effect of female labor force participation is similar to the baseline result in column 4 of Table 3 (−0.07), it is not statistically significant at the conventional level (p value 0.109). Given that the negative effect is strong and significant in group B (−0.25), a smaller and insignificant effect of female employment in group A suggests that either the bargaining effect does not exist or it is dominated by backlash or extraction motives of men.

In summary, while I find no convincing evidence on the labor market outcome effect, the exposure reduction effect seems to be a major underlying mechanism through which female labor force participation reduces spousal violence. Although the backlash or extraction effects appear to be present and plausibly dominate the bargaining effect, the overall effect of female working is still negative, suggesting that the exposure reduction effect exceeds the counteracting backlash or extraction effects.

5.4 District level results

I conduct the same analysis at the district level to allow for more variations in the instrument.[17] For the district level analysis, I use136 districts over seven different rice states.[18] Since the rice–wheat dichotomy—dummy for being in a rice state—does not vary within the rice states, I use the rice–wheat ratio in each district to construct the instrument. Rice–wheat ratio is defined by the rice area divided by the sum of the two areas—rice area / (rice area + wheat area). Further, rainfall shocks are defined by the difference of the yearly rainfall from the normal rainfall (30-year average) at the district level, scaled by standard deviation. The other control variables in the regression are as defined by Eqs. 1 and 2, except that the state level covariates are replaced by the district level covariates.

Table 6 reports the district level OLS and instrumental variable estimation results regarding the effect of female employment on the probability of spousal

[17] Although NFHS-2 does not provide a district level identifier, the districts can be identified based on Census of India 1981 and 1991. The district identifier is provided by Alessandro Tarozzi.

[18] Seven rice states include Andhra Pradesh, Assam, Bihar, Madhya Pradesh, Maharashtra, Orissa, and West Bengal. The other five states – Karnataka, Kerala, Manipur, Meghalaya, and Tamil Nadu – are dropped due to lack of crop area information at the district level.

Table 6 District level OLS and IV estimates of the effect of female employment by sub-group

Sub-group	All		Group A (Compensation)		Group B (Non-compensation)		Group C (Husband non-agriculture)	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
Controls								
Female employment	0.0258	−0.2587	0.0305	−0.2522	−0.0009	−0.5617	0.0119	0.6198
	(0.0126)**	(0.1062)**	(0.0134)**	(0.1033)**	(0.0186)	(0.2871)**	(0.0465)	(1.9153)
No. of observation	5,869		5,649		3,835		756	

Robust standard errors are in parenthesis

**Significant at 5%

violence. The results are consistent with the state level analysis in Tables 3 and 5.[19]

The naïve OLS regression suggests that female employment is associated with a greater risk of violence towards them (column 1). Once instrumented, however, it reduces the probability of spousal violence by 0.26 (column 2), which is stronger and more precise than the estimate in Table 3 (-0.07).

The remaining heterogeneous effects by sub-group are also consistent with the previous reports in Table 5. There is no significant evidence on the labor market outcome effect (column 8). On the other hand, the negative effect of female employment using group B in column 6 (−0.56) suggests the presence of the exposure reduction effect. Further, the effect of employment among women with compensation (group A) is negative, but smaller (−0.25) than the effect among group B. This suggests the presence of backlash or extraction motives towards women with financial resources, although they seem to be exceeded by the exposure reduction effect, given that the overall effect is still significantly negative (column 2).

5.5 Other results

I further investigate the effect of female contributions to the household income on their violence experience. I do not report the estimation results for the sake of brevity, but summarize the main findings in the following.[20]

According to the theory of marital bargaining, women with more financial resources are expected to have higher bargaining power, which would eventually reduce the probability of spousal violence. The instrumental variable estimation result, however, does not support the bargaining story. An exogenous increase in the degree of women's income contributions has an insignificant effect on the probability of violence towards them. This result is consistent with the heterogeneous effects among the sub-groups in Sections 5.3 and 5.4, which find no evidence on the bargaining effect.

5.6 Discussion

The empirical analysis of this study provides important policy implications in addressing issues of spousal violence. First, an increase in financial resources of women without effective exposure reduction might adversely affect violence

[19]Similarly, the first stage regression result shows that more rain fall shocks in a district with higher rice-wheat ratio improve the probability of female labor force participation. This result is not reported for brevity.

[20]In this analysis, I use the categorical variable for female income contribution explained in footnote 15, and additionally include women who do not work by assigning 0 to them. The instrument for the female contribution is again the interaction between rainfall shocks and the rice–wheat dichotomy at the state level. The assumption behind the identification strategy is similar to the case of female working status, in that the degree of female income contribution exogenously increases when there are more rainfall shocks in the rice-growing area.

against women. This might be the case, especially in a patriarchal cultural setting, where husbands' motives for backlash or extraction are likely to increase in response to higher financial independence of women. Second, the exposure reduction effect associated with female employment effectively reduces spousal violence. These findings, therefore, suggest that increasing labor force participation of women, thereby decreasing the exposure to risk of violence, would be more effective than a direct monetary transfer to women.

In this study, I do not find convincing evidence on the bargaining effect of female employment or income contribution. Further, I find little empirical support for higher violence-reporting as a labor market outcome. The interpretation of such findings, however, requires caution, particularly because those findings might be a direct result of the limitations of the instrument. In identifying the effect of labor force participation on the incidence of violence, I use short term weather shocks as a source of identification. Given that bargaining power within the household would not depend on transitory changes (Duflo 2003), it might not be surprising that little evidence is found on the bargaining effect. It cannot be ruled out that suggestive evidence on backlash or extraction exists, because those effects are more sensitive to short-term changes, whereas the bargaining effect is more responsive to long-term changes. Similarly, if higher violence-reporting is driven by permanent changes in labor market outcomes, rather than short-term changes, lack of evidence on the labor market outcome effect might be due to the nature of the identification strategy. Therefore, future research needs to address whether permanent changes in labor market outcomes of women generate the same results as are obtained in this study.

6 Conclusion

In this study, I identify the effect of labor force participation of women on spousal violence in rural India. The identification strategy exploits changes in labor market outcomes of rural women, driven by rainfall shocks interacted with the rice–wheat dichotomy. I find that female labor force participation decreases the probability of physical spousal violence. Although there is some evidence supporting the backlash or extraction effects, the effects are dominated by the exposure reduction effect. On the other hand, I find no convincing evidence on the bargaining effect. The results, therefore, suggest the exposure reduction is a key element in policy interventions on spousal violence in the short run.

The findings of this study emphasize the importance of understanding cultures and social norms of a local area in implementing development policies. Without such understanding, policies to empower women might end up disempowering them. For desirable outcomes, we need to design a more sophisticated development policy that incorporates efforts to minimize conflicts with existing social norms.

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Appendix 1

Table 7 Spousal violence experience of women in the past 12 months by work status

Work status	Work	Do not work
Violence in the past 12 months		
No	28,037 (89.19%)	50,798 (903.16%)
Yes	3,398 (10.81%)	3,732 (6.84%)
Total	31,435 (100%)	54,530 (100%)

NFHS-2 1998–1999

Appendix 2

Rural economic and demographic survey 1998–1999

Rural Economic and Demographic Survey (REDS) 1998–1999 is collected by the National Council of Applied Economic Research in India and covers about 7,500 rural households over 250 villages in 16 states of India. Out of 18 states included in the main sample, REDS has data on 14 states. The two states that are not included in REDS are Manipur and Meghalaya. The dataset contains detailed information on household agricultural labor and production, as well as demographic characteristics.

REDS is used in this study to show the rice–wheat dichotomy in female employment (Fig. 1). Further, it provides information on work days for agricultural laborers by gender and household agricultural labor income, both of which are not included in NFHS-2, but important for testing exclusion restrictions. For males, reported work days of 1,747 male agricultural laborers aged over 16 in landless households over 13 states are used for the regression result in column 6 of Table 2. The regression equation is defined by Eq. 2, except for the dependent variable being male work days. For females, reported work days of 267 female agricultural laborers aged over 16 in landless households over 10 states are used for the result in column 7 of Table 2.

In addition, household labor income is obtained by adding the wages of all of the household members who earn agricultural wages in a landless household. Again, the regression equation is the same as defined by Eq. 2, except for the dependent variable being household labor income. After dropping some households with missing variables on demographic variables or village level covariates, I find 606 households over 13 states. The estimation result is reported in column 5 of Table 2.

District wise area and production of principal crops in India by directorate of economics and statistics

District wise Area and Production of Principal Crops in India provides district-level crop data. The Directorate of Economics and Statistics, for the first time in 2001, published this brochure that includes comprehensive data on district wise area and production of principal crops in India for 1997–1998 and 1998–1999. I use 136 district-level crop data for seven rice states—Andhra Pradesh, Assam, Bihar, Madhya Pradesh, Maharashtra, Orissa, and West Bengal. The other five states in the rice-growing area are dropped, because their districts do not match the districts of NFHS-2.

APHRODITE project

Rainfall data for the district level analysis is a rain-gauge-based 0.5° daily grid precipitation product developed by the Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE). The dataset contains interpolated rainfalls for a series of $0.5 \times 0.5°$ grids covering Asia. I map all rainfall data into each district in India. Then, the district level rainfalls are calculated by averaging all the gridded rainfall information within one district. Rainfall shocks are defined by the difference of yearly rainfalls from the normal rainfall (30-year average) at the district level, scaled by standard deviation. Again, I use 136 district level rainfall shocks over seven rice states.

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