

Statistical Analysis of Rainfall Insurance Payouts in Southern India

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Abstract

Using 40 years of historical rainfall data, this paper estimates a distribution for payouts on rainfall insurance policies offered to farmers in the State of Andhra Pradesh, India, in 2006. The authors find that the contracts primarily protect households against extreme tail events; half the expected value of indemnities paid by the insurance are generated by only 2 percent of rainfall

realizations. Contract payouts are significantly correlated cross-sectionally, and also inversely associated with real GDP growth. The paper discusses the implications of these findings for the potential benefits of insurance to households, the risks facing a financial institution underwriting rainfall insurance contracts, and pricing.

This paper—a product of the Finance and Private Sector Development Team, Development Research Group—is part of a larger effort in the group to study microinsurance products. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The author may be contacted at xgine@worldbank.org.

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1. Introduction

Exposure to drought among rural households in India and other countries should, at least in principle, be largely diversifiable. This is because rainfall is exogenous to the household and not likely to be strongly correlated with the systematic risk factors, such as aggregate stock returns, that are relevant for a well-diversified representative investor.

With this principle in mind, the goal of rainfall index insurance is to allow households, groups and governments to reduce their exposure to weather risk by purchasing a contract that pays an indemnity during periods of deficient (or excessive) rainfall. Advocates argue that index insurance is transparent, inexpensive to administer, enables quick payouts, and minimizes moral hazard and adverse selection problems associated with other risk-coping mechanisms and insurance programs (see World Bank 2005; Barnett and Mahul 2007; Giné, Townsend, and Vickery 2007).

This paper uses historical rainfall data to estimate the distribution of payouts on a rainfall index insurance product developed by the general insurer ICICI Lombard and offered to rural Indian households since 2003. Our empirical strategy draws on the observation that rainfall in the region we study is close to a stationary process. Correspondingly we can use historical rainfall data to calculate a putative history of insurance payouts for insurance contracts written against the 2006 monsoon.

We conduct several statistical exercises to better understand the properties of estimated insurance payouts. First, we study the probability distribution of indemnities. Does the insurance contract pay off regularly, providing income during periods of moderately deficient rainfall? Or does it operate more like disaster insurance,

infrequently paying an indemnity, but providing a very high payout during the most extreme rainfall events? Our evidence suggests the truth is closer to the second case. Analyzing 14 insurance policies, each linked to a different rainfall gauge, we estimate the average probability of receiving a payout on a single phase of insurance coverage is only 11 percent. The maximum indemnity, paid with a probability of around 1 percent, provides a rate of return to the policyholder of 900 percent. We also find that insurance premiums are on average around three times as large as expected payouts.

Second, we study the correlation of payouts in the cross-section and through time. Spatially correlated rainfall shocks may be more difficult for households to insure against through other means, such as informal risk-sharing arrangements within local kinship groups. This in turn implies larger benefits of a formal rainfall insurance contract. On the other hand, dependence in payouts may also increase the balance sheet exposure of ICICI Lombard or their reinsurers to rainfall risk, by reducing the diversification benefits of holding a pooled portfolio of insurance contracts. Research in corporate finance argues that exposure to risk may reduce firm value when there are informational problems or other frictions in raising external finance (e.g., Froot, Scharfstein, and Stein 1993).

We find no evidence of temporal dependence in payouts. However, it is estimated that rainfall insurance payouts are significantly positively correlated across contracts at a point in time, perhaps unsurprising given that we study policies linked to rainfall within a single geographic region of India. Even so, it is estimated that there are still significant risk-reduction benefits from holding a diversified portfolio of contracts. The standard

deviation of payouts on an equally weighted basket of 11 different insurance policies is only half as large as the standard deviation of an average individual contract.

Third, we find some evidence that insurance payouts are negatively correlated with growth in India's per capita GDP. This suggests that some component of rainfall risk is aggregate to the Indian economy as a whole, perhaps reflecting the size and importance of the Indian agricultural sector for employment and economic activity.

2. Background and Methodology

We study a rainfall insurance product developed by the general insurer ICICI Lombard, which has been offered to rural Indian households since 2003. ICICI Lombard partners with local financial institutions to market the insurance to households. Giné, Townsend, and Vickery (2007) and Cole and Tufano (2007) provide detailed background about the insurance product. Giné, Townsend, and Vickery (2007) also study the determinants of household insurance purchase decisions, based on a 2004 household survey.

Our analysis focuses on calendar year 2006 insurance contracts linked to rainfall in the southern Indian state of Andhra Pradesh. Below, we briefly summarize the design of these contracts. Policies cover rainfall during the Kharif (monsoon season), which is the prime cropping season running from approximately June to September. The contract divides the Kharif into three phases roughly corresponding to sowing, podding/flowering and harvest. The first two phases are 35 days in duration, while the third (harvest) phase is 40 days long. In 2006, farmers were allowed to purchase different numbers of contracts across each of the three phases.

Phase payouts are based on accumulated rainfall between the start and end dates of the phase, measured at a nearby reference weather station or rain gauge.¹ The start of the first phase is triggered by the monsoon rains. Namely, phase 1 (sowing) begins on the first date on which accumulated rain since June 1 exceeds 50mm, or on July 1 if accumulated rain since June 1 is below 50mm.

Insurance payouts in the first two phases are linked to low rainfall. The payout structure in these cases is illustrated in figure 1. Contract details in the figure are from the phase 1 contract linked to the Mahabubnagar weather station, which is representative of the policies studied in our empirical analysis. The policy pays zero if accumulated rainfall during the phase exceeds an upper threshold, or ‘strike’, which in this case is 70mm. Otherwise, the policy pays Rs. 10 for each mm of rainfall deficiency relative to the strike, until the lower threshold, or ‘exit’, is reached. If rainfall is below the exit value, the policy pays a fixed, higher indemnity of Rs. 1000. Phase 3 policies have the same structure, but in reverse, they pay out only when rainfall exceeds the strike, meant to correspond to unusually heavy rainfall during the harvest that causes damage to crops.

Depending on the policy, the reference weather station is one of three types: an Indian Meteorological Department (IMD) station, mandal rainfall station (a mandal is a local geographic area roughly equivalent to a U.S. county) or one of a network of automated rain gauges installed by ICICI Lombard. For this paper, we focus on IMD

¹ Some adjustments are made to accumulated rainfall when constructing the rainfall index used to calculate payouts. If daily rainfall exceeds 60mm, only 60mm is counted towards the cumulative rainfall index. Also, rainfall <2mm is ignored. These adjustments reflect that heavy rain may generate water runoff, resulting in a less than proportionate increase in soil moisture, while very light rain is likely to evaporate before it soaks into the soil. We take these adjustments into account when constructing putative insurance payouts.

rainfall data. These are considered to be more reliable than data from mandal stations, and include a longer and more complete history of past rainfall to construct a putative dataset of insurance payouts.

Our source data consist of policy terms for contracts indexed to 14 different IMD weather stations in Andhra Pradesh (one contract per station), as well as IMD historical rainfall data for each station. Rainfall data are measured at a daily frequency. Although the earliest rainfall data is from 1970, the starting point of the data varies by weather station, and there are also scattered individual months and years where data is missing. Across 14 stations, there are 1,089 individual contract phases for which at least some rainfall data is available. However, for 135 phases data is missing for at least one day during the contract period. We drop these from our analysis, leaving a sample of 954 phases for which we have complete daily rainfall to calculate payouts.

The amount of missing data varies significantly across weather stations. At one extreme there are 91 phases of complete rainfall data for the Anantapur weather station (equivalent to 30.3 monsoon years). At the other extreme, for the Adilabad and Nalgonda stations, only a small number of complete phases of rainfall data is available (8 and 18 phases respectively). At least 64 phases (21.3 monsoon years) of complete daily historical data is available for 11 of the 14 stations; our empirical findings are similar if we restrict analysis to these stations only.

Applying the insurance contract terms to historical rainfall data, we calculate the hypothetical payout on the contract for each station, phase and year. Data on estimated payouts and information on contract features are presented in table 1. Strikingly, the

insurance pays an indemnity in only 10.7 percent of phases, a point we return to below. The average estimated payout is Rs. 29.7, compared to an average premium of Rs. 99.9. This wedge presumably reflects, at least in part, the administrative and financing costs of designing, underwriting and selling insurance policies, especially given the small current size of the market and lack of associated economies of scale. Although the insurance is not actuarially fair, it may still be valuable to policyholders if it pays an indemnity in times when the household's marginal utility of consumption is particularly high.

3. Distribution of Payouts

Evidence on the distribution of payouts is presented in figure 2. The x-axis for the graph is 'payout rank,' which ranks payouts in increasing order of size, expressed on a scale from 0 to 1. Figure 2 plots payout amount against payout rank. The payout is zero up to the 89th percentile, indicating that an indemnity is paid in only 11 percent of phases. The 95th percentile of payouts is around Rs. 200, double the average premium. In a small fraction of cases (around 1 percent), the insurance pays the maximum indemnity of Rs. 1000, yielding an average return on the premium paid of 900 percent.

Figure 2 suggests that the ICICI Lombard policies we study primarily insure farmers against extreme tail events of the rainfall distribution. Confirming this graphical evidence, we calculate that around one-half of the value of indemnities is generated by the highest-paying 2 percent of phases. Without further evidence on the sensitivity of household consumption to rainfall shocks of different types, it is difficult to say whether this structure approximates the optimal insurance design. For example, Paxson (1992) and Jacoby and Skoufias (1998) are generally unable to reject that consumption of rural

households in Thailand and India respectively is fully insured against rainfall fluctuations. However, these two papers do not consider whether the degree of consumption insurance is lower for extreme shocks, such as a severe drought, which could for example exhaust the household's stock of precautionary savings.

From the perspective of ICICI Lombard, the skewed distribution of payouts suggests a significant reserve of liquid funds may need to be held against policies whose risk is not transferred to reinsurers. This in turn could be costly due to informational frictions in raising external finance or tax disadvantages in holding capital (Zanjani 2002; Froot 1999; Froot and Stein 1998). Amongst other factors, the insurer's exposure to risk will depend on the value of policies originated, the extent to which reinsurance is used, and correlation of insurance payouts across contracts and through time. We present some evidence on these correlations in the next section.

4. Dependence on Insurance Payouts

To calculate the degree of cross-sectional dependence in payouts, we calculate the standard deviation of phase payouts for each weather station, restricting analysis to the 11 contracts for which we have the most historical rainfall data. The average of these 11 estimated contract standard deviations is Rs. 112.3. We then calculate the standard deviation of the mean insurance payout averaged across the 11 stations at each point in time. This standard deviation will in general be smaller than 112.3, reflecting the diversification benefits from pooling a portfolio of contracts whose returns are not perfectly correlated. If insurance payouts are independent, the standard deviation of the mean payout will asymptotically be $1/\sqrt{11}$ times as large as the standard deviation of

individual contract payouts (i.e. $1/\sqrt{11} \times 112.3 = \text{Rs. } 33.9$, a reduction in the standard deviation of 70 percent). In contrast, if payouts are perfectly correlated across contracts, there would be no difference between the standard deviation of the mean payout and those of the individual contracts.

Empirically, we calculate that the standard deviation of the mean payout is Rs. 60.7, 46 percent smaller than the average standard deviation of individual contract payouts. This reduction in the standard deviation is smaller than 70 percent, indicating that insurance payouts are positively correlated cross-sectionally. However, there are still surprisingly large diversification benefits from holding a portfolio of insurance contracts, even though all insurance payouts are driven by rainfall in the same Indian state. Diversification would be larger still if contracts are pooled over a wider geographic area.

An alternative approach to estimating the insurer's exposure to rainfall risk is to compute extreme quantiles of portfolio exposures, such as the 95th or 99th percentile of losses. This methodology, known as value at risk (VaR), is widely used by financial risk managers. See Saunders and Cornett (2006) for a textbook introduction to VaR. For our sample, the 99th percentile of the distribution of mean insurance payouts is Rs. 412. This is 13.6 times larger than the mean insurance indemnity, and 4.1 times larger than the mean insurance premium. In contrast, the 95th percentile of mean insurance payouts is Rs. 130, while the 75th percentile is only Rs. 30. These results indicate that the distribution of mean insurance payouts is highly skewed, in keeping with the distribution of individual contract payouts presented in Figure 2, and that extreme rainfall events produce losses several times in excess of phase insurance premia collected.

ICICI Lombard could employ a variety of strategies to ensure sufficient funds are available to pay claims in case of extreme rainfall events, such as holding a precautionary buffer of liquid assets, securing a bank line of credit, or selling part of their risk exposure to a reinsurer. In practice, even though only a modest number of policies have been written to date, ICICI Lombard has indicated to us that they do use reinsurers to limit their exposure to rainfall risk. Costs associated with these risk-mitigation strategies may be one explanation for why insurance is priced at a premium to actuarial value.

Next, we estimate a simple autoregressive model to examine the time-series correlation in insurance payouts. These estimates are of interest because persistent rainfall shocks may be more difficult for households to smooth. (For example, under a permanent income model, the sensitivity of consumption to current income shocks is increasing in the persistence of the shock.) In addition, temporal dependence in rainfall and payouts may allow insurance purchasers to take advantage of a kind of ‘stale pricing’ opportunity. If weather patterns are persistent, rainfall shocks after insurance premia are fixed by ICICI Lombard would shift the actuarial value of the contract relative to the premium. A household could take advantage of this lack of price updating by delaying its purchase decision until just before the start of the phase, and adjusting their insurance demand in light of updated weather information. Zitzewitz (2006) provides empirical evidence of a related kind of ‘late trading’ behavior amongst U.S. mutual fund investors.

We estimate two simple autoregressive models. The dependent variable in both models is the phase insurance payout. In the first model this variable is simply regressed on lagged phase payouts. In the second model we include two additional rainfall variables

that may be useful predictors of insurance payouts: a dummy variable indicating whether lagged payouts are greater than zero, and cumulative rainfall in the previous phase. (Since we regress phase payouts on variables lagged one phase, we estimate these two regressions for payouts on the second and third phases of the monsoon only.)

Results are presented in Table 2. In both regressions, the degree of persistence in payouts is economically small and not statistically significant. Furthermore, neither of the additional lagged variables included in the second model are significantly correlated with insurance payouts. For our sample, the fact that variables based on current rainfall have little predictive power for future insurance payouts perhaps suggests that the ‘stale pricing’ issue discussed above is not a significant concern in practice.

5. Correlation with Aggregate Variables

Finally, we estimate correlations between insurance indemnity payouts and several aggregate variables, including GDP growth, inflation and stock returns. Such correlations could plausibly be non-zero, because rainfall shocks are spatially correlated within India, and the agricultural sector represents a significant fraction of Indian output and employment. Therefore, extreme rainfall events may represent a non-trivial productivity shock for the overall Indian economy.

Our estimates of these correlations are presented in Table 3. The first part of the table estimates bivariate and multivariate correlations between insurance payouts and several Indian macroeconomic variables measured at an annual frequency: growth in Indian GDP per capita, the inflation rate, and the change in the short-term and long-term

Indian Treasury yield. Depending on the variable, either 30 or 38 years of data is available for this exercise. Regression standard errors are clustered by year.

Insurance payouts are found to be negatively correlated with growth in Indian GDP per capita, significant at the 10 percent level in the bivariate regression and the 5 percent level in the multivariate model. Economically, a 1 percentage point fall in GDP growth is associated with an increase in payouts of Rs. 4-5, around 15 percent of expected insurance payouts. Insurance payouts reflect only the tail of rainfall realizations; in unreported regressions we also find that GDP growth is negatively correlated with phase rainfall, significant at the 1 per cent level. None of the other macroeconomic variables are significantly correlated with rainfall insurance payouts, however.

Results in table 3 provide some evidence that measured payouts, beyond being spatially correlated within Andhra Pradesh, are also correlated with aggregate Indian economic activity. This suggests that remittances to drought-stricken areas from family members in other parts of India may provide only incomplete sharing of risk associated with extreme rainfall events, since transfers within risk-sharing groups cannot smooth shocks that are aggregate to the group (Townsend 1994). The finding also potentially strengthens the case for ICICI Lombard to hedge its exposure to weather risk arising from rainfall insurance. The balance sheet of a foreign reinsurer is likely to be less exposed than ICICI Lombard to Indian macroeconomic risk.

The last part of table 3 displays the correlation of insurance payouts with Indian SENSEX stock market returns. For each year and station we calculate stock returns between the start and end dates of each insurance phase, then convert them to an

annualized rate. Thus, returns match up exactly to the period covered by the contract, rather than just the year of the contract, as for the macroeconomic data. Payouts are not significantly correlated with Indian stock returns, however, perhaps reflecting that most Indian agricultural output is produced by small farms, rather than large traded firms.

6. Conclusions

This paper has used historical rainfall data to estimate a putative history of payouts on Indian rainfall insurance policies. We have found that indemnities are concentrated in the extreme tail of adverse rainfall events. This insures households against severe shocks, but it also creates a highly skewed distribution of losses for an insurer writing rainfall insurance policies. This balance sheet exposure can be partially ameliorated by holding a portfolio of geographically segmented insurance contracts, or by using reinsurance markets.

We emphasize that much more research is needed to evaluate the promise of weather index insurance. For example, to shed further light on welfare benefits and to inform optimal contract design, theoretical and empirical work is needed to improve our understanding of the types of weather shocks against which rural household consumption is not well insured.

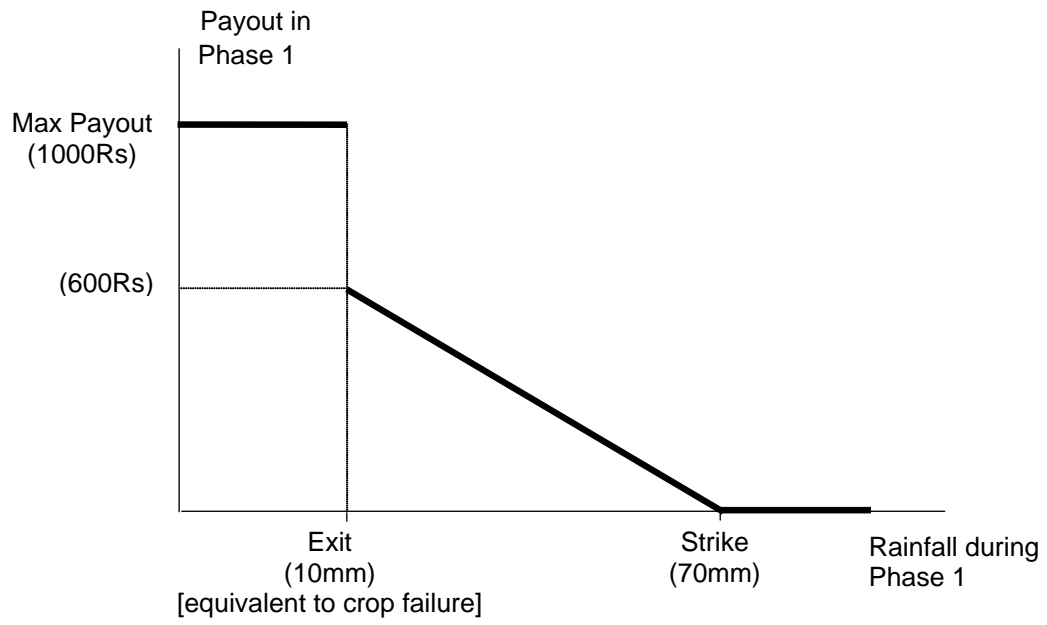


Figure 1. Structure of insurance contract

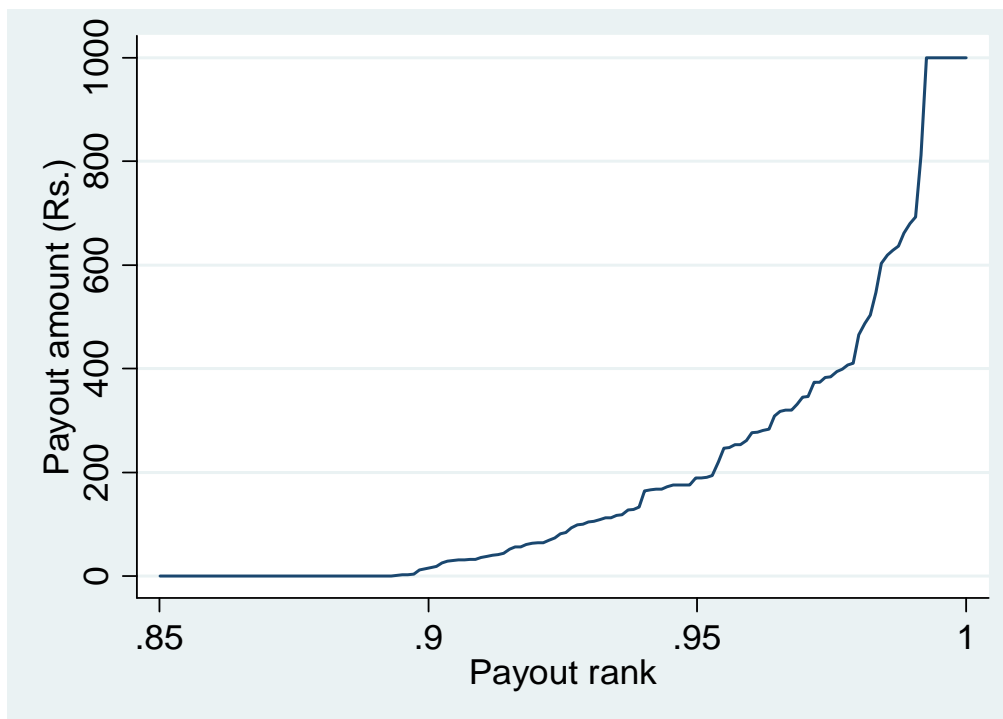


Figure 2. Distribution of insurance payout amounts

Table 1. Summary Statistics of Rainfall Insurance Payouts

| | average payout | percent positive payouts | average premium | mean rainfall index | Average triggers | | Number of obs. (phases) |
|-------------------|-------------------|--------------------------------|--------------------|---------------------------|---------------------|------------|-------------------------------|
| | | | | | strike | exit | |
| Phase One | 20.9 | 13.7 | 98.3 | 176.0 | 78 | 15 | 322 |
| Phase Two | 46.4 | 13.0 | 102.8 | 192.9 | 72 | 12 | 316 |
| Phase Three | 22.0 | 5.4 | 98.5 | 211.6 | 499 | 580 | 316 |
| All phases | 29.7 | 10.7 | 99.9 | 193.4 | n/a | n/a | 954 |

Note: Table relates to rainfall insurance contracts written against 14 IMD rainfall stations in Andhra Pradesh, India, in 2006. Estimates of average payouts are based on historical IMD rainfall data from 1963-2000 and 2004-2006. Note that in all cases, insurance contracts pay out Rs. 10 per mm of rainfall deficiency relative to the ‘strike’, until the ‘exit’ is reached. Beyond the exit (i.e., below the exit in the case of Phases 1 and 2, and above the exit for Phase 3), the insurance pays out a fixed indemnity of Rs. 1000.

Table 2. Time Series Dependence in Insurance Phase Payouts

| Lagged variables | bivariate | multivariate |
|--|------------------|-------------------|
| <i>Intercept</i> | 34.4*** (9.4) | 46.5** (19.0) |
| <i>Insurance Payout (Rs.)</i> | 0.017 (0.04) | 0.004 (0.05) |
| <i>Dummy for positive payout [0,1]</i> | | -3.214 (17.25) |
| <i>Phase rainfall (mm)</i> | | -0.061 (0.07) |
| R ² | 0.000 | 0.002 |
| N | 603 | 603 |

Note: Dependent variable is insurance phase payout. The regression sample consists of estimated putative insurance payouts relating to phases 2 and 3. These are regressed on explanatory variables which are lagged by one phase. Numbers in parentheses are standard errors, which are clustered by time period (i.e., phase interacted with year). ***, **, and * indicate two-sided statistical significance at the 1 percent, 5 percent and 10 percent level respectively.

Table 3: Correlation of Insurance Payouts with Aggregate Variables

| Variable name | macroeconomic variables | | | | | stock returns |
|--|-------------------------|--------|-------|--------|-------|---------------|
| <i>GDP growth (percent change, real</i> | -4.19* | | | | | -5.41** |
| <i>GDP per capita)</i> | (2.21) | | | | | (2.54) |
| <i>Inflation (percent change, GDP</i> | | 0.26 | | | | -1.65 |
| <i>deflator)</i> | | (1.02) | | | | (1.16) |
| <i>Change in Treasury bond yield (1-5</i> | | 0.24 | | | | -0.02 |
| <i>year maturity)</i> | | (2.49) | | | | (2.08) |
| <i>Change in Treasury bond yield (></i> | | | | 3.77 | | 3.48 |
| <i>15 year maturity)</i> | | | | (8.66) | | (9.04) |
| <i>India SENSEX index</i> | | | | | | -0.02 |
| | | | | | | (0.05) |
| R ² | 0.011 | 0.000 | 0.000 | 0.000 | 0.015 | 0.000 |
| Number of observations | 922 | 922 | 871 | 871 | 871 | 657 |
| Years of data, RHS variable | 38 | 38 | 30 | 30 | 30 | 23 |

Note: Dependent variable is insurance phase payout. Numbers in parentheses are standard errors, which are clustered by year, except for stock returns, which are clustered by time period (i.e., phase interacted with year). ***, **, and * indicate two-sided statistical significance at the 1 percent, 5 percent and 10 percent level respectively. All regressions also include a constant term.

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