

Dynamics of Demand for Index Insurance: Evidence from a Long-Run Field Experiment[†]

By SHAWN COLE, DANIEL STEIN, AND JEREMY TOBACMAN*

In the past ten years, many practitioners and academics have embraced micro-insurance. Economists view risk diversification as one of the few readily available “free lunches,” and dozens of products were launched in the hopes of developing a financial service that was both welfare enhancing and economically sustainable. A successful market-based approach, however, requires consumers to make good decisions about whether to purchase products. Practically speaking, because marketing policies is expensive, sustainability may depend on high purchase and repurchase rates.

From a consumer perspective, making optimal insurance decisions requires a high degree of sophistication. Consumers must correctly estimate the probability distribution over a wide range of states of the world and imagine alternative coping mechanisms which may be available in unfamiliar scenarios. These difficulties are likely to be even more pronounced with novel financial products, such as rainfall index insurance, whose payouts depend on readings at local rainfall stations rather than consumers’ actual losses. Reactions to others’ experience may also be an important determinant of the commercial success of these products.

* Cole: Harvard Business School, Soldiers Field, Boston, MA, 02163, and NBER (e-mail: scole@hbs.edu); Stein: The World Bank, 1818 H Street NW, Washington, DC 20433 (e-mail: dstein@worldbank.org); Tobacman: University of Pennsylvania, 3620 Locust Walk, Philadelphia, PA 19104, and NBER, (e-mail: tobacman@wharton.upenn.edu). We are very grateful to Chhaya Bhavsar, Nisha Shah, Reema Nanavaty, and their colleagues at SEWA, whose extraordinary efforts made this research possible. Maulik Jagnani, Laura Litvine, Dhruv Sood, Sangita Vyas, Will Talbott, Nilesh Fernando, and Monika Singh provided excellent research assistance. AIC offered useful insight and coordination on product design. We would also like to thank USAID’s BASIS program, 3ie, IGC, and Wharton’s Dean’s Research Fund for financial support. All errors are our own.

[†] Go to <http://dx.doi.org/10.1257/aer.104.5.284> to visit the article page for additional materials and author disclosure statement(s).

This paper examines the development of a new insurance market in detail, using a seven-year panel of rainfall insurance purchase decisions made by rural farming households in Gujarat, India. We characterize the evolution of take-up rates. We show that demand is highly sensitive to payouts being made in a household’s village in the most recent year: a payout of Rs 1,000 (ca. US\$20, or roughly five days wage labor income) increases the probability households purchase insurance in the next year by 25–50 percent. This effect is robust to controlling for crop losses, suggesting that insurance experience, rather than weather shocks, drives increased purchasing. This effect is stronger when more individuals in a village receive payouts. However, there is little additional effect of a household actually receiving a payout in the most recent season, once we condition on village payouts. This suggests that information generated by insurance payouts has village-wide effects.

We also explore the effects of insurance payouts over a longer time period. We find the effects of payments being made in a village remain positive over multiple seasons, but the estimated size decreases over time. In the most recent year, a household’s receipt of an insurance payout does not have an additional effect beyond payments being made in the village, but longer-lagged household payout experience (two and three years before the current purchase decision) does have a strong positive effect on the purchasing decision.

These results stand in contrast to standard rational models, in which the realization of recent insurance outcomes should not affect forward-looking insurance decisions. Our findings from rural India are consistent with the findings by Kunreuther, Sanderson, and Vetschera (1985) and Browne and Hoyt (2000), who study earthquake insurance purchases and flood insurance purchasers, respectively.

Gallagher (forthcoming) examines a long-term community-level panel of flood insurance coverage in the United States, and finds that insurance demand increases after a recent flood, but this effect decreases over time. In developing country contexts, Karlan et al. (2013) show, in a two-year panel, that rural Ghanaians are more likely to purchase if they or people in their social networks received payouts in the previous year. Hill, Robles, and Ceballos (2013) find positive effects of insurance payouts on future purchasing in India. Dercon et al. (2014) and Mobarak and Rosenzweig (2013) study how insurance demand interacts with existing informal insurance arrangements, while Cai and Song (2013) compare the impacts of hypothetical scenarios and recent disaster experience on weather insurance demand. Perhaps most closely related to our work is Stein (2011), which uses a three-year panel of rainfall insurance sales in southern India to estimate strong effects of receiving insurance payouts but limited spillover effects.

This paper represents the first attempt we are aware of to study the dynamics of demand for a product in which learning may be important, over a long time period (seven years), with randomized shifts in demand. Our richer data allow us to separately identify the dynamic effects of living in a village where payouts are made from the effects of an individual actually receiving payouts. The effect of living in a village with payouts is strongest in the subsequent season, while the individual-level effect of receiving a payout is strongest after two or three years.

I. Experimental Setting

For the study, a Gujarat-based NGO, the Self-Employed Women's Association (SEWA) marketed rainfall insurance to residents of 60 villages over a seven-year period from 2006 to 2013. The rainfall insurance policies, underwritten by insurance companies with long histories in the Indian market, provided coverage against adverse rainfall events for the summer ("Kharif") monsoon growing season. Households must opt-in to repurchase each year to sustain coverage. A SEWA marketing team visited households in our sample each year in April–May to offer rainfall insurance policies.

Each year households in the study were randomly assigned marketing packages, which induced exogenous variation in insurance

coverage. The offering varied from year to year, and included discounts, targeted marketing messages, and special offers on multiple policy purchases. The effects of these marketing packages on insurance purchasing at the start of the study period are described in Cole et al. (2013). In addition, from 2009 through 2013, we elicited households' willingness to pay for insurance using an incentive-compatible Becker-deGroot-Marschak (BDM) mechanism, which both induces exogenous variation in take-up and yields high-resolution data on households' insurance demand. Further details of the marketing interventions can be found in the online Appendix.

At the beginning of the project in 2006, SEWA introduced rainfall insurance in 32 villages in Gujarat. In 2007, access was extended to 20 additional villages.¹ These 52 villages were randomly chosen from a list of 100 villages in which SEWA had a substantial preexisting operational presence.² Within each study village, 15 households were surveyed, of which five were randomly selected SEWA members, five had previously purchased (other forms of) insurance from SEWA, and five were identified by local SEWA employees as likely to purchase insurance. Since take-up of insurance was expected to be low, those thought likely to purchase insurance were deliberately oversampled. In 2009, 50 households in each of eight additional villages were added to the study. Cumulatively, the sample that has been surveyed and assigned to receive insurance marketing by SEWA consists of 1,160 households in 60 villages. We restrict analysis in this paper to the balanced panel of households who remain available to receive both marketing and survey visits in each year after they are added to the project. This results in a main sample of 989 households and 5,659 household-years in which the current and once-lagged insurance coverage decision are observed.

The terms of the insurance coverage offered each year varied due to changes in the insurance market and SEWA's desire to offer the best possible coverage to its members as it learned

¹ Other than via SEWA's initiative, rainfall insurance has in practice been unavailable in the study area.

² The other 48 villages serve as control villages for a parallel randomized controlled trial of the effects of rainfall insurance.

about their rainfall-related risk. However, the coverage had certain stable features. It was written based on rainfall during the June–September Kharif growing season. Contracts depended upon daily rainfall readings at local rainfall stations, and specified payouts as a function of cumulative rainfall during fixed time periods. Conditions indicative of drought and flood were covered. The smallest indivisible unit of insurance, which we refer to here as a “policy,” generally had a maximum possible payout of Rs 1,500. Households were free to purchase multiple policies to achieve their desired level of coverage. More details of the specific policies offered can be found in the online Appendix.

II. Data

Our data are merged from two primary sources. Administrative information on insurance purchasing decisions was provided by SEWA. This includes the number of policies purchased and the rupee amount of payouts disbursed. The second data source is an annual household survey. The survey has been extensive, but here we use it only to ensure that attrition is detected and to construct one useful covariate, the household-level crop loss experienced.

Each season, households were asked if they had experienced crop loss due to weather. If they answered yes, the amount of crop loss is calculated as the difference between that year’s agricultural output and the mean value of output in all prior years where crop loss was not reported. Summary statistics for all variables are reported in the online Appendix.

III. Empirical Analysis

A. OLS Estimates

Throughout this section we report estimates of regressions of an insurance purchase indicator on lagged measures of insurance experience.³

Table 1 considers separately the sample of insurance purchasers (i.e., those who had purchased in the previous year) and the sample of insurance non-purchasers (i.e., those who had

not purchased in the previous year) to gain a simple view of direct versus spillover effects of past insurance payouts. Columns 1 and 2 consider the insurance purchasers, consisting of the 882 households who purchased insurance at least once over the years 2006–2012, with a total of 2,085 household-year observations. Column 1 shows the OLS relationship⁴ between insurance purchase in the current year and the payout per policy in the previous year in the village (which depends only on the terms of the contract and measurements at the reference weather station). This regression (along with all that follow) includes household fixed effects and clusters standard errors at the village level.⁵ The coefficient on the Village Payout Per Policy is statistically and economically significant, implying that a payout per policy of Rs 1,000 causes a 50 percentage point increase in the probability of purchasing insurance in the next season.

The actual payout received by a household is the payout per policy times the number of policies purchased. In column 2 we add variables for the number of policies purchased in the previous year, the total payout received in the previous year, and three additional controls: Number of Households in Village who Received a Payout the Previous Year, the household’s Revenue Lost Due to Crop Loss the Previous Year, and the Mean Revenue Lost Due to Crop Loss in the village the previous year. None of these variables enter significantly, and the coefficient on Village Payout Per Policy remains strong and significant.

In columns 3 and 4 we turn to the non-purchasers of insurance in order to concentrate on spillover effects. These regressions show that past insurance payouts have a strong effect even on people who had not purchased insurance, and this effect is stronger if more people in the village have received payouts. In column 3, the coefficient suggests that an increase in payout of Rs 1,000 leads to a 26 percentage point larger chance of purchasing insurance the following year among non-purchasers. The point estimates of the effect of insurance payouts are roughly twice the size of those for non-purchasers, but we cannot statistically reject their equality.

³ This paper focuses on effects of the level of recent insurance payouts. Of course, optimal insurance decisions would be informed by the joint distribution of payouts and indemnities (i.e., crop losses).

⁴ Throughout the paper, for simplicity, we report results from linear probability models.

⁵ Robustness is extensively documented in the online Appendix.

TABLE 1—EFFECTS OF PAYOUTS ON PURCHASERS AND NON-PURCHASERS

| | Insurance purchasers | | Insurance non-purchasers | |
|--|----------------------|--------------------|--------------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| Village payout per policy in previous year (Rs '000s) | 0.504*** (0.139) | 0.513** (0.196) | 0.255** (0.107) | 0.196* (0.105) |
| Individual payout received previous year (Rs '000s) | | -0.046 (0.046) | | |
| Number of insurance policies bought previous year | | 0.014 (0.014) | | |
| Number of households in village who received a payout previous year | | 0.003 (0.002) | | 0.005*** (0.002) |
| Revenue lost due to crop loss previous year (Rs '0,000s) | | -0.011 (0.016) | | -0.004 (0.011) |
| Mean village revenue lost due to crop loss previous year (Rs '0000s) | | 0.027 (0.049) | | 0.063 (0.040) |
| Individual fixed effects | Yes | Yes | Yes | Yes |
| R ² | 0.167 | 0.171 | 0.187 | 0.196 |
| Observations | 2,085 | 2,085 | 3,574 | 3,574 |

Notes: The “insurance purchasers” sample is restricted to insurance purchasers at some point between 2006 and 2012, with households entering and exiting the sample each year based on their prior year insurance purchase decisions. This sample consists of 882 households who purchased insurance at least once. The “insurance non-purchasers” sample is restricted to households who did not purchase insurance at some point between 2006 and 2012, with households entering and exiting the sample each year based on their insurance purchase decisions. This sample consists of 977 households, as 12 households purchased insurance in each year that it was available and are therefore always excluded. The dependent variable is a dummy for purchasing insurance in current year. All specifications include individual fixed effects, year dummies, dummies for when the household entered the experiment, and the complete set of same-year and previous year’s marketing variables as additional controls. All specifications are OLS, and all standard errors are clustered at village level. Additional related specifications can be found in Tables A1 and A2 of the online Appendix.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

B. IV Analysis

In this section we present the results for the combined sample. In the IV specifications, we instrument for the lag of the number of insurance policies purchased and the amount of payouts received using variables characterizing the lagged marketing packages and interactions of the lagged marketing packages with lagged insurance payouts.

Column 1 of Table 2 presents the primary IV specification. The coefficient on Village Payout Per Policy is large and significant, suggesting that an increase in payout by Rs 1,000 results in a 29 percentage point increase in the probability of purchasing insurance the following year. The coefficient on the Individual Payout is positive, but not significantly different than zero. In column 2 we include on the right-hand side the Number of Households in Village who Received a Payout the Previous Year, the individual

household’s Revenue Lost Due to Crop Loss the Previous Year, and the Mean Revenue Lost Due to Crop Loss in the village the previous year. The coefficient on the Number of Households in Village who Received a Payout the Previous Year is significant, implying that for each additional household receiving a payout, the probability of other villagers purchasing rises by 0.3 percentage point. The Village Payout effect remains strong and significant. In sum, these IV results are largely consistent with the OLS results in Table 1. Insurance payouts have large effects on purchasing decisions in the following year.

C. Longer-Term Effects

We now exploit the panel’s long duration. Figure 1 plots the coefficients of an IV regression which is the same as above, except that the purchasing decision is regressed on

TABLE 2—EFFECTS OF INSURANCE PAYOUTS ON FULL SAMPLE

| | Full sample | |
|--|---------------------|---------------------|
| | IV (1) | IV (2) |
| Village payout per policy in previous year (Rs '000s) | 0.293*** (0.092) | 0.266*** (0.092) |
| Individual payout received previous year (Rs '000s) | 0.114 (0.079) | 0.09 (0.074) |
| Number of insurance policies bought previous year | 0.00 (0.010) | 0.001 (0.010) |
| Number of households in village who received a payout previous year | | 0.003** (0.001) |
| Revenue lost due to crop loss previous year (Rs '0000s) | | -0.015* (0.008) |
| Mean village revenue lost due to crop loss previous year (Rs '0000s) | | 0.035 (0.031) |
| Individual fixed effects | Yes | Yes |
| Cragg-Donald F-Stat | 26.24 | 25.899 |
| R ² | 0.166 | 0.17 |
| Observations | 5,659 | 5,659 |

Notes: Regressions include the full study sample of 989 households for all years in which they received insurance marketing. All specifications include individual fixed effects, year dummies, a dummy for the year in which a household entered the experiment, and the complete set of same-year marketing variables as additional controls. “Payout Received Previous Year” and “Number of Insurance Policies Bought Previous Year” are instrumented with the full set of marketing variables lagged one year, and the marketing variables interacted with village insurance payouts. All specifications are OLS, and all standard errors are clustered at village level. Additional related specifications can be found in Table A4 of the online Appendix.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

three lags of village and individual payouts.⁶ Consistent with our estimates above, the village payouts in the most recent year have a large effect while the additional effect of receiving a payout oneself is small. However, for two- and three-year lags the estimated effect of the village payout decreases, while the estimated effect of the individual payout increases. In the second

⁶ This distributed lag specification is restricted to the 3,861 observations where three lags are observed for the household. For comparability with the main IV results, we include the same set of right-hand-side controls, plus two additional lags of the Number of Policies Bought. Three lags of marketing package variables are used as exogenous instruments. For more details see the online Appendix.

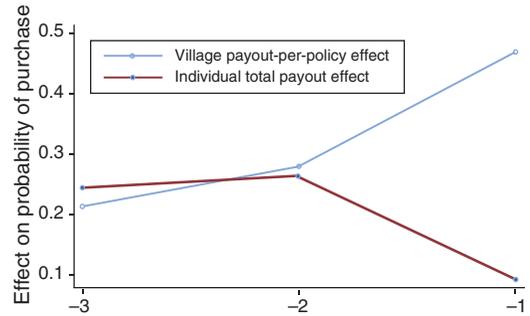


FIGURE 1. LONGER-TERM EFFECTS OF PAYOUTS

Notes: This figure plots the estimated effects on the insurance purchase probability of three lags of village-level payouts per policy and three lags of individual-level total payouts received, per 1,000 rupees of past payout. All estimates are significantly different than zero apart from the estimate on the first-year lag of individual payouts received. Estimates are drawn from specifications which instrument for past individual payouts with three lags of variables characterizing SEWA's randomly-assigned marketing packages, entered both directly and interacted with the village payout per policy. Regressions also include three lags of the number of insurance policies purchased (also instrumented), individual crop loss, and village average crop loss, as well as individual fixed effects, year dummies, a dummy for the year in which a household entered the sample, and the complete set of same-year marketing variables. The sample is restricted to households that received insurance marketing for the three previous seasons before the current purchase decision. The regression table is presented in the online Appendix Table A5.

and third year, the effects are statistically indistinguishable, meaning that the effects of payouts are around twice as large for those who actually receive them versus people who simply live in a village where payouts were made.

IV. Discussion

Taken together, the following patterns emerge. First, across almost all specifications there is a large and significant effect of having insurance payouts in a village on purchasing decisions the next year. This effect holds both for the insurance purchasers themselves (who received payouts) and the non-purchasers (who did not receive payouts). People are also more likely to purchase if many village coresidents received payouts in the previous year, a finding that is robust to controlling for revenue lost due to crop failure (which might have been expected to tighten liquidity constraints the following

year). These results suggest that the transmission mechanism of the payouts is through dissemination of knowledge, as opposed to wealth or liquidity effects. By contrast, Stein (2011) concluded that the actual receipt of payouts was driving repurchase decisions.

When considering insurance purchasers and non-purchasers separately, we find the effect of insurance payouts in the previous year is roughly twice as large for the insurance purchasers. However, when considering the sample together and instrumenting for past household experience, the difference in effects decreases and is insignificant. The difference in these results may simply be due to noise: we cannot reject the hypothesis that the effects of payouts for purchasers and non-purchasers are the same. However, it is also possible that those whose purchases were caused by marketing packages behaved differently. The OLS results in Table 1 reflect the behavior of all insurance purchasers, of whom the compliers are a subset. That self-selected insurance purchasers are more likely to be affected by payouts is consistent with a form of “confirmation bias” among people with high demand for insurance. Receiving payouts makes them feel justified in their decision to purchase insurance (even at higher prices), and this drives future purchases. This effect is absent for people who were induced to purchase insurance by discounts and other marketing features.

The long-term results are more nuanced. We find that the effects of a village payout persist over three years, yet decrease in magnitude over time. This is consistent with the results of Gallagher (forthcoming), who shows that insurance purchasing is consistent with a Bayesian learning model only allowing for rapid forgetting about past disasters. Over-inference from recent experience is another explanation for the data. Surprisingly, we find the additional effect of a household’s own payout experience follows a different pattern. While the first lag of receiving a payout is small and insignificant, the effect of the second and third lags is large. The difference in lagged effects of witnessing a payout versus receiving one is curious and merits further investigation.

V. Conclusion

This paper provides new evidence about the evolution of demand for a promising but

complicated micro-insurance product. We find that households in villages where insurance payouts occurred are much more likely to purchase in the following season. This effect persists for multiple seasons but decreases over time. We find that the additional effects of experiencing a payout oneself are small for the first season after the payouts are made, but are larger two and three seasons later. Overall, our results suggest some updating from insurance experience, with spillovers that are transmitted to non-purchasers of insurance.

These findings have mixed implications for the prospects of rainfall index insurance. Large spillovers can facilitate commercial expansion. However, over-inference from recent payouts (analogous to return-chasing with insurance viewed as an investment, c.f. Slovic et al. 1977) might distort individual decisions. High variance in the expansion rates of rainfall index insurance across time and space, depending on recent experiences, might also result. We hope this analysis can usefully complement and inform leading practical thinking about the public and private sector roles in agricultural insurance (Mahul et al. 2013).

REFERENCES

- Browne, Mark J., and Robert E. Hoyt.** 2000. “The Demand for Flood Insurance: Empirical Evidence.” *Journal of Risk and Uncertainty* 20 (3): 291–306.
- Cai, Jung, and Changcheng Song.** 2013. “Insurance Take-up in Rural China: Learning from Hypothetical Experience.” Unpublished.
- Cole, Shawn, Xavier Gine, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery.** 2013. “Barriers to Household Risk Management: Evidence from India.” *American Economic Journal: Applied Economics* 5 (1): 104–35.
- Dercon, Stefan, Ruth Vargas Hill, Daniel Clarke, Ingo Outes-Leon, and Alemayehu Seyoum Taffesse.** 2014. “Offering Rainfall Insurance to Informal Insurance Groups: Evidence from a Field Experiment in Ethiopia.” *Journal of Development Economics* 106: 132–43.
- Gallagher, Justin.** Forthcoming. “Learning About an Infrequent Event: Evidence from Flood Insurance Take-up in the US.” *American Economic Journal: Applied Economics*.

- Hill, Ruth Vargas, Miguel Robles, and Francisco Ceballos.** 2013. "Demand for Weather Hedges in India: An Empirical Exploration of Theoretical Predictions." IFPRI Discussion Paper 01280.
- Karlan, Dean, Robert Darko Osei, Isaac Osei-Akoto, and Christopher Udry.** 2013. "Agricultural Decisions after Relaxing Credit and Risk Constraints." National Bureau of Economic Research Working Paper 18463.
- Kunreuther, Howard, Warren Sanderson, and Rudolf Vetschera.** 1985. "A Behavioral Model of the Adoption of Protective Activities." *Journal of Economic Behavior and Organization* 6 (1): 1–15.
- Mahul, Oliver, Daniel Clarke, Barry Maher, and Fatou Assah.** 2013. "Promoting Access to Agricultural Insurance in Developing Countries." Unpublished.
- Mobarak, Ahmed Mushfiq, and Mark R. Rosenzweig.** 2013. "Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries." *American Economic Review* 103 (3): 375–80.
- Slovic, Paul, Baruch Fischhoff, Sarah Lichtenstein, Bernard Corrigan, and Barbara Combs.** 1977. "Preference for Insuring against Probable Small Losses: Insurance Implications." *Journal of Risk and Insurance* 44 (2): 237–58.
- Stein, Daniel.** 2011. "Paying Premiums with the Insurer's Money: How Loss Aversion Drives Insurance Decisions in a Repeated Interaction." Unpublished.