Hedging by Giving: Spiritual Insurance and Religious Donations

Yu-Jane Liu, Juanjuan Meng, Dalin Sheng, Guangxin Yang, and Yu Zhang*

Abstract

We investigate "spiritual insurance"—a mental strategy for coping with risk, where individuals engage in good deeds, including donations, in exchange for perceived blessings and protection. Using bank transactional data, we show that higher income uncertainty and health shocks lead to increased donations, particularly to religious charities. Moreover, individuals who donate to religious charities tend to reduce insurance expenditures. In a field experiment on millions of potential donors through an online platform, we find that spiritual insurance narratives increase giving, providing direct causal evidence for such a motive. Our findings provide new evidence on how spiritual insurance affects household risk-coping behavior.

*Liu, yjliu@gsm.pku.edu.cn, Peking University Guanghua School of Management; Meng, jumeng@gsm.pku.edu.cn, Peking University Guanghua School of Management; Sheng, shengdl@swufe.edu.cn, Southwestern University of Finance and Economics; Yang, ygx@stu.pku.edu.cn, Peking University Guanghua School of Management; Zhang (corresponding author), yuzhang@gsm.pku.edu.cn, Peking University Guanghua School of Management. We thank Sumit Agarwal, Doug Bernheim, John Beshears, Kyle Chauvin, James Choi, Hanming Fang, Drew Fudenberg, James Hines, David Hirshleifer, Harrison Hong, Silong Li, Ragan Petrie (discussant), Eva Raiber, Collin Raymond, Alberto Rossi, Yang Su, Huan Tang, Hui Wang (discussant), Roberto Weber, Wei Xiong, Erez Yoeli, Shirley Xin Zou (discussant), and seminar and conference participants at NYU Shanghai, Peking University, SWUFE, UIBE, Xiamen University, ABFER, AMES Tsinghua, AMES Singapore, China Behavioral and Experimental Economics Forum, CCER Summer Institute, CICF, CFRC, IIPF, Stanford SITE Psychology and Economics, and Tsinghua Alumni Economics Workshop for their valuable suggestions. We gratefully acknowledge the financial support of the National Natural Science Foundation of China (grant numbers 72172004, 72204009, 72225002, 72394393, 72503198). All authors contributed equally to this work. All errors are our own.

Whoever is kind to the poor lends to the LORD, and will be repaid in full.

—(New International Version, Proverbs 19:17)

1. Introduction

Uncertainty plays a pivotal role in economics and finance. Traditionally, it is managed through material means such as savings, diversification, and insurance. Yet, people also use psychological, religious, or spiritual strategies to cope with uncertainty. For example, ancient sailors prayed to deities like Poseidon for protection at sea, reflecting faith in supernatural intervention. Today, megachurches in the U.S. encourage donations by suggesting such acts may invite blessings and help avert misfortune (Bowler, 2013). This concept of *spiritual insurance*—the belief that good deeds, such as donations, bring blessings or protection from future risks—serves as a potential psychological hedge against risk, which may influence household finance decisions.

Past work links religious and auspicious beliefs to financial behaviors, including stock participation, investments, and corporate decisions (Hong, Kubik, and Stein, 2004; Kumar, 2009; Hilary and Hui, 2009; Hirshleifer, Jian, and Zhang, 2018; Bhattacharya et al., 2018). Recent studies have documented a substitution effect between charitable donations and insurance (Dehejia, DeLeire, and Luttmer, 2007; Auriol et al., 2020; Cronqvist, Warachka, and Yu, 2023). Among them, Auriol et al. (2020) randomize funeral insurance in Ghana and show insurance reduces giving to both churches and spiritual goods, supporting the spiritual insurance hypothesis. However, direct evidence for the underlying spiritual insurance mechanism remains limited, evidence on spiritual insurance behavior in response to broader and more common risks such as income uncertainty and health shocks is scarce, and whether spiritual insurance is still relevant in markets with ready access to formal insurance tools is unclear.

In this paper, we test spiritual insurance predictions using high-frequency transaction data on income, donations, and insurance purchases from over 70,000 individuals at a Taiwanese bank. Analyzing within-person variations, we find that increased income uncertainty and health shocks predict higher donations, especially to religious or spiritual charities, which are in turn negatively associated with insurance purchases. These results provide the first evidence that spiritual insurance operates in response to income and health shocks. We complement this with a large-scale field experiment on 4 million donors conducted by an online donation platform in mainland China. Exposure to spiritual insurance narratives causally increases donation rates, providing direct causal evidence for the underlying spiritual insurance mechanism in real behavior.

We first outline a stylized model of donation and insurance behaviors with or without spiritual insurance to derive testable predictions. Spiritual insurance is modeled as donations shifting perceived probabilities of income states, reducing bad outcomes and increasing good ones. Without spiritual insurance, income uncertainty reduces donations through an income effect. With strong spiritual insurance beliefs, income uncertainty increases donations. The model also predicts donations and insurance function as substitutes, where donations with a spiritual insurance interpretation associated with lower insurance demand. These relationships provide testable implications for the spiritual insurance hypothesis.

We test model predictions using transaction data from a major Taiwanese bank covering income, donations, and insurance for over 70,000 individuals between July 2013 and June 2015 with direct payroll deposits and regular credit card use. We observe the donations they made mostly to non-local philanthropic foundations, some connected with a religion or spiritual tradition.[1] The dataset provides a suitable laboratory for testing spiritual insurance. Crucially, recipient foundations are not local churches, serve beneficiaries (e.g., children in poverty, disaster relief) distinct from donors, and credit card donations in Taiwan are primarily made online.[2] These features suggest our dona-

[1]Most donations to religious charities in the dataset are directed to evangelical philanthropic foundations, suggesting that our results may have relevance for regions with evangelical presence.

[2]More than three-quarters of credit card donations in Taiwan are made online, according to survey results from the Taiwan Nonprofit Self-Regulation Alliance, accessible at https://tinyurl.com/5yvmepar or https://tinyurl.com/mwzruacs in English. In addition, we provide a list of all the philanthropic foundations in our dataset, religious or secular, and describe the details of their nature and beneficiaries in

tions may not function as informal mutual insurance at the community level. The insurance data enable examining associations between spiritual insurance and conventional risk management.

We have three major findings from the bank transaction data. First, within-person increases in income uncertainty, measured by the standard deviation of unanticipated income shocks, a common proxy for background risk (Heaton and Lucas, 2000; Angerer and Lam, 2009; Betermier et al., 2012), predict higher donations. A one standard deviation increase raises donations by 0.37 times the sample mean, significant at the 1% level. To ensure that our measure of income uncertainty is not unduly influenced by an employee's individual labor supply decisions and to address potential measurement errors, we examine the robustness of our findings through an instrumental variable approach, instrumenting individual-level uncertainty with leave-one-out, firm-level average uncertainty. The IV approach confirms that income uncertainty predicts higher donations.

Second, consistent with spiritual insurance, income uncertainty predicts higher donations to foundations connected with a religion or spiritual tradition ("religious donations", broadly defined), and such a relationship also exists for other adverse shocks such as health shocks. Income uncertainty predicts higher donations 52% more strongly for religious donations than for secular ones.[3] Negative income uncertainty particularly drives religious donations. We also study how health shocks, which are adverse events that could potentially influence future uncertainty, relate to donation behavior. We find that health shocks (medical expenses above median in the prior quarter) are associated with an increase in donations by 1.46 times the sample mean, especially religious donations, aligning with spiritual insurance predictions.

Third, conditional on donating, people spend less on insurance, and insurance spend-

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Online Appendix A.1.

[3]Census data from Taiwan show 56% of religious donors cited "seeking blessings" as motivation versus 22% for secular donations (Survey on Social Development Trends, Directorate-General of Budget, Accounting and Statistics, https://srda.sinica.edu.tw/search/metadata/detail/AA200006, report at https://tinyurl.com/mvznsx96 or https://tinyurl.com/2vbtjwn4). The predominantly evangelical nature of recipient foundations reinforces this interpretation.

ing no longer relates to background risks. Within-person, donating to religious or spiritual foundations at least once in a quarter is associated with a 42% decrease in insurance purchases, with each dollar of religious donation linked to a \$5 reduction in insurance spending. While a one standard deviation increase in income uncertainty is associated with a \$102 increase in insurance expenditures, this effect appears mitigated when employees donate to foundations connected with a religion or spiritual tradition that quarter. These patterns hold even for individuals unlikely to be financially constrained. At the monthly frequency, religious donations predict lower insurance expenditures in the following month. This temporal pattern provides suggestive evidence that donation behavior may causally affect insurance expenditures. Furthermore, the insurance reduction concentrates among experienced buyers at the annual-renewal decision and among individuals without prior observed insurance purchases who are deterred from first-time entry, with no significant rebound in the post-donation quarters.

Interestingly, we find no evidence that donations materially reduce future income uncertainty, suggesting that spiritual insurance may reflect wishful thinking that does not translate into tangible outcomes. However, we cannot exclude the psychological comfort that such behaviors may provide.

We next test whether our findings uniquely support spiritual insurance by examining the model's quantitative implications and alternative explanations. Under plausible parameters of relative risk aversion around 4 and moderate probability shifts, our results match predictions from both the baseline model and its insurance extension. We assess mutual insurance, altruism, seasonality, and taxes. The non-local nature of recipient foundations and absence of consumption-insurance benefits reduce the likelihood of informal mutual insurance. Stronger effects for religious donations and negative donation-insurance association suggests that increased altruism alone may not fully account for our findings. Controlling for seasonal income and tax rates leaves results unchanged, reinforcing the spiritual insurance interpretation of the bank transaction findings.

To directly study spiritual insurance narratives' influence in the field at a large scale, we analyze a field experiment by one of the world's leading charity crowdfunding platforms in mainland China from July 28 to August 15, 2022 that involved 4 million potential donors. Treatment donors, randomly assigned, saw an "accumulate good spiritual connections to receive karmic blessings" message beneath the donation button. This subtle intervention was designed to enhance spiritual insurance salience. Two results were observed, which both aligned with spiritual insurance predictions. First, the message appears to significantly increase donation likelihood. Second, variations in regional responsiveness were observed, positively correlated with local pre-exposure to spiritual narratives.

These experimental results suggest spiritual insurance narratives tangibly affect behavior. Consistency across observational and experimental settings offers some evidence for the external validity, as support for spiritual insurance is observed across contexts. Together, the bank transaction and field experiment evidence are jointly consistent with the hypothesis that spiritual insurance may play a role in influencing mental management of risk, charitable giving under risk, and insurance decisions.

Our study relates to several research lines. First, we build on work examining finance and religion. Hong, Kubik, and Stein (2004) show church attendance predicts stock market participation, suggesting social networks lower information costs. Religious norms discouraging gambling reduce corporate investment (Hilary and Hui, 2009) and lottery-stock investment (Kumar, 2009). While prior work emphasizes social networks and norms, we investigate spirituality as spiritual insurance—an individualistic exchange with a higher power—that may influence risk-coping behaviors, enriching the religion-finance framework.

Within the religion-finance literature there is also an emerging literature concerning insurance. Research has shown that church donations (Dehejia, DeLeire, and Luttmer, 2007) and religious attendance (Chen, 2010) help smooth shocks through mutual insurance. Cronqvist, Warachka, and Yu (2023) find that more crop insurance use reduces church participation in the U.S. Closest to our study, Auriol et al. (2020) randomized funeral insurance among Ghanaian churchgoers, showing insurance crowds out both local church giving and donations to non-mutual-insurance ends, providing causal evidence of substitution consistent with spiritual-insurance motives.[4] Building on these findings, we use high-frequency bank transaction data on income, giving, and insurance purchases to provide the first evidence for spiritual-insurance behavior in response to daily risks like income uncertainty and health shocks. We observe this mechanism holds in Taiwan and mainland China, contexts with easy access to formal financial insurance, thus extending prior evidence from lower formal insurance supply settings. Our field experiment directly manipulates a spiritual-insurance narrative, finding increased giving, especially where spiritual belief is stronger, providing direct evidence of the mechanism that complements prior substitution evidence.

Third, our study contributes to the household finance literature on behavior under income uncertainty and health risk. Research shows individuals respond through reducing financial market risk exposure (Guiso, Jappelli, and Terlizzese, 1996, Heaton and Lucas, 2000, Betermier et al., 2012, Choi and Robertson, 2020, d'Astous and Shore, 2024), informal community risk-sharing (Townsend, 1994), and formal insurance markets (Guiso and Jappelli, 1998, Koijen, Van Nieuwerburgh, and Yogo, 2016).[5] For a review, see Gomes, Haliassos, and Ramadorai (2021). We provide large-scale evidence that spiritual insurance may serve as a psychological mechanism for coping with income uncertainty and health risk.[6]

[4]Malinowski's classic study found that Trobriand Islanders performed religious rituals when facing uncertain (dangerous) outcomes (like deep-sea fishing), but not for safe, predictable tasks, consistent with spiritual insurance (Malinowski, 1922).

[5]Studies document auspicious beliefs affecting behavior under uncertainty: Hirshleifer, Jian, and Zhang (2018) and Bhattacharya et al. (2018) show people align investments with lucky numbers; He et al. (2020) find fewer housing transactions on inauspicious days and higher prices for lucky numbers; Fisman et al. (2023) report firms reduce R&D and acquisitions in the chairman's zodiac year.

[6]We also contribute to the literature on donation motives (review: Andreoni and Payne, 2013), which documents effects of taxes (Auten, Sieg, and Clotfelter, 2002), pure altruism (Becker, 1974), warm-glow (Andreoni, 1989), inequality aversion (Fehr and Schmidt, 1999), reciprocity (Falk, 2007), and social image (DellaVigna, List, and Malmendier, 2012). We provide evidence for spiritual insurance as a donation motive under income uncertainty and health risk. While this literature predicts donations should decline with income uncertainty, spiritual insurance predicts the opposite pattern we observe.

The rest of the paper proceeds as follows. Section 2 presents a stylized model deriving testable implications. Section 3 introduces the bank transaction dataset, constructs the income uncertainty measure, describes the empirical specification, reports estimates on how within-person income uncertainty predicts donations, and tests the spiritual insurance channel through religious donations and insurance purchases. Section 4 details the field experiment on spiritual insurance narratives. Section 5 concludes.

2. Model

To derive the testable predictions, we first analyze a stylized model in which donations provide direct utility (non-insurance motive) and can also alter perceived probabilities of income states (spiritual insurance motive), so individuals behave as if their giving may influence uncertain outcomes. The baseline model considers income uncertainty and donations; we later extend it to include medical expense risk and insurance purchases.

The agent faces uncertain income $\tilde{I}$, realized as $\bar{I} - D$ (bad) and $\bar{I} + D$ (good) with probability p each, or $\bar{I}$ (neutral) with probability $1 - 2p$. Before observing income, the agent chooses donation g, yielding utility $E(u(\tilde{I} - g)) + \theta v(g)$, where $v(g)$ is the direct (non-insurance) utility from giving.[7] Both $u(\cdot)$ and $v(\cdot)$ are increasing, strictly concave, and $u(\cdot)$ has positive prudence $(u'''(\cdot) > 0)$.[8]

We compare two models: one without, and one with, a spiritual insurance motive. Absent spiritual insurance, optimal donation g^* declines as background risk D rises:

Lemma 1 *In the model without the spiritual insurance motive, the optimal donation size g^* decreases with background risk D. (Proof in Online Appendix A.)*

[7]This builds on Auriol et al. (2020) by considering two-sided income risk and later, medical risk.

[8]Positive prudence is weaker than DARA. Our data also show that higher income uncertainty increases insurance purchases, in line with this.

In the model with a spiritual insurance motive, the agent maximizes:

$$\max_g (1-2\bar{p})u(\bar{I}-g) + (\bar{p}-\pi(g))u(\bar{I}-g-D) + (\bar{p}+\pi(g))u(\bar{I}-g+D) + \theta v(g). \tag{1}$$

The function $\pi(g)$ captures how donations shift perceived probabilities: higher g reduces the perceived chance of a negative income shock ($\bar{I}-D$) and raises the perceived chance of a positive one ($\bar{I}+D$). While finance research typically understands insurance as protection against negative outcomes, spiritual insurance is broader, as it also includes the promotion of positive outcomes. These beliefs are central to spiritual insurance: the agent perceives that charitable actions (i.e., donations) can influence uncertain outcomes in their favor.

A positive relationship between optimal donation and background risk D ($\frac{\partial g^*}{\partial D} > 0$) holds if:

$$\begin{aligned} &\pi'(g^*)\left[u'\left(\bar{I}-g^*+D\right)+u'\left(\bar{I}-g^*-D\right)\right] \\ &> \left[\bar{p}-\pi(g^*)\right]\left[-u''\left(\bar{I}-g^*-D\right)\right]-\left[\bar{p}+\pi(g^*)\right]\left[-u''\left(\bar{I}-g^*+D\right)\right]. \end{aligned} \tag{2}$$

Economically, the left-hand side ($\equiv \pi'(g)\frac{\partial}{\partial D}[u(\bar{I}-g+D)-u(\bar{I}-g-D)]$) is the increased marginal benefit from the spiritual insurance effect: as D rises, the utility gap between good and bad states widens, amplifying the effect of shifting subjective probabilities. The right-hand side is the income effect: greater uncertainty raises the expected marginal cost of donations.

Weighing the benefits and costs, when the spiritual insurance effect outweighs the income effect (i.e., condition (2) holds), we have a key prediction summarized in Proposition 1:[9]

Proposition 1 *If the spiritual insurance channel is sufficiently strong, i.e., condition (2) holds, then in the model with a spiritual insurance motive, the optimal donation g^* in-*

[9]Condition (2) is easily met. It holds in 94.7% of reasonable parameter combinations in our simulations (Online Appendix A.3, Figure A.1).

creases with background risk D. (Proof in Online Appendix A.)

Such a prediction contrasts with Lemma 1, where uncertainty reduces donations in the standard model absent spiritual insurance.

Thus, estimating the relationship between donations and income uncertainty could generate insights that help differentiate the spiritual insurance motive. Finding a null or negative relationship would imply that this motive is weak or absent. Conversely, a positive relationship between donations and income uncertainty would suggest the presence of a sufficiently strong spiritual insurance motive in donations.

Motivated by the observation that our data includes insurance purchases in addition to donations, we propose an extended model that incorporates expense risks (alongside income risks) and insurance purchases. We present the setup and proofs of the extended model in Online Appendix A.4.

This extension generates new testable predictions about the interaction between donations and insurance. As summarized in Proposition A.1: if the spiritual insurance channel is strong (under a condition similar to (2)), increasing donations may reduce the need for market-based insurance, as donations could potentially lower the perceived risk of a low-income state, and vice versa. If the spiritual insurance channel is weak or absent, this relationship is reversed.

Guided by the above discussion of the baseline and the extended model, we proceed to empirically examine the relationship of donations with income uncertainty, as well as the relationship between donations and insurance purchases.

3. Bank Transaction Data Analysis

3.1 The Data

We use detailed anonymized bank records from employees of firms using a major commercial bank (hereafter the Bank) in Taiwan for payroll direct deposits. The dataset covers all transaction types (e.g., checking, credit card, investment, insurance) and includes transaction records, monthly balances, and demographic information, enabling us to examine links between income uncertainty, donations, and insurance purchases.

The Bank data span July 2013 to June 2015. We analyze full-time workers aged 18–55, employed at firms using the Bank for consecutive payroll direct deposits over the 24-month period, who also use the Bank's credit card.[10] The final sample comprises 74,023 individuals with records on payroll, credit card spending, and insurance purchases. To address the infrequent occurrence of donation and insurance transactions, we aggregate data to the individual-quarter level, yielding 592,184 observations.

Table 1 reports summary statistics. Online Appendix Table A.1 provides the variable definitions. The average and median monthly payroll incomes in the sample are 4,067 USD and 2,200 USD, respectively. This median income is above the census median of 1,200 USD, suggesting that our sample may represent a group of individuals with potentially greater access to financial services.[11] Due to the right-skewed income distribution, we use the logarithm of payroll income and related uncertainty measures in our analysis.

[Table 1 here]

We observe donations made by individuals as part of their credit card transactions. The proportion of clients who donated during the sample period is 6.27%. Furthermore, 2.09% of all individuals in the sample donated in more than one quarter. Observations with a non-zero donation amount account for 1.46% of the sample at the individual-quarter level.

These credit card donations are made to philanthropic foundations, which in our dataset are not local churches or their central offices. Under law, these foundations are required to use funds for general social welfare and are prohibited from providing direct benefits to specific individuals, including the donors themselves.[12] Consequently, the

[10] We include only individuals earning at least the minimum wage (635 USD per month) to confirm full-time status; 55 is the minimum legal retirement age. Limiting to pre-retirement age allows us to measure genuine income uncertainty, not expected changes due to retirement.

[11] https://ws.dgbas.gov.tw/win/fies/doc/result/104.pdf

[12] https://law.moj.gov.tw/ENG/LawClass/LawAll.aspx?pcode=D0050138.

beneficiaries, such as children in poverty or recipients of disaster relief, are unrelated to the donors, making mutual insurance at the local community level unlikely. Additionally, most credit card donations are made online in Taiwan, further limiting their potential to facilitate local mutual insurance.

Foundations receiving credit card donations in our dataset are classified as religious or spiritual if their mission explicitly states religious goals or if their name clearly references a religion or spiritual tradition. All others are classified as secular. Among individual-quarter donation observations, 61% donated to religious or spiritual foundations and 42% to secular foundations, with some donating to both in the same quarter. Further details on these foundations are provided in Online Appendix A.1.

The conditional average amount of donations to foundations connected with a religion or spiritual tradition ("religious donations," broadly defined) is 94.39 USD, and the conditional average amount of donations to secular foundations ("secular donations") is similarly 94.40 USD. Each amount represents approximately 0.80% of the sample's average quarterly income, which is a non-negligible share.

Because Taiwan's National Health Insurance mainly covers minor health issues, private insurance plays a crucial role for major medical expenses and made up 29.6% of national health expenditure in 2021 (Pu, Lee, and Hsieh, 2023). In our data, we observe the type and amount of each insurance purchase. Approximately 90% are critical illness or life insurance products; we exclude savings and investment-oriented insurance, which account for the remaining 10%. Nearly half of clients (45.3%) purchased insurance during the period, representing 13.4% of individual-quarter observations; The conditional average amount spent on market-based insurance products was 1569.40 USD.[13]

[13]Although the share of donors (6.27%) is lower than the insurance purchase rate (45.3%), this is consistent with the nature of the donations recorded. Our bank records capture only credit-card donations to foundations; cash donations are unobserved, so the observed rate is a conservative lower bound. Because our identification relies on within-person variation, omitting offline donations affects levels but not estimated percentage responses to income uncertainty, rendering our (level) estimates conservative.

3.2 Measuring Individual-Level Income Uncertainty

Our main independent variable is income uncertainty, a key concept in household finance (e.g., Viceira, 2001; Lustig and Van Nieuwerburgh, 2005; Betermier et al., 2012; Bonaparte, Korniotis, and Kumar, 2014). We specifically examine how this uncertainty, formed through each individual's recent experience, *predicts* donation behavior. Our dataset quantifies both income level (the first moment) and income uncertainty (the second moment). In our model, holding the first moment of income fixed, an increase in the second moment of income predicts lower or higher donations depending on whether the spiritual insurance motive is weak or strong.

To quantify income uncertainty, we use the volatility of realized income over a recent period as a proxy. We calculate income uncertainty for each individual-quarter observation as the standard deviation of all monthly income realizations from the preceding four quarters. We show later that this proxy significantly predicts future income uncertainty (Section 3.5). Following the literature (e.g., Angerer and Lam, 2009, Jurado, Ludvigson, and Ng, 2015), we residualize monthly income realizations to remove predictable components (e.g., seasonal effects or demographic trends) that may not constitute "uncertainty."[14] This involves regressing log payroll income against observable characteristics and removing the predictable component:

$$y_{im} = \alpha + \mathbf{X}'_{im}\beta + \mu_m + \varepsilon_{im} \tag{3}$$

where y_{im} is the log monthly payroll income of individual i in month m; $\mathbf{X}_{im}$ includes demographic characteristics (city of residence, age, age squared, marital status, education, occupation, number of dependents); and μ_m is a time fixed effect. We focus on the residuals $\hat{\varepsilon}_{im}$, which represent the unpredicted component of income.

The income uncertainty measure for each individual-quarter observation, $\hat{\sigma}_{i,t-1}$, is the standard deviation of monthly payroll income residuals, $\hat{\varepsilon}_{im}$, over the recent period

[14] Results using raw payroll income are similar (untabulated).

M_{t-1}:

$$\hat{\sigma}_{i,t-1} = sd_{m \in M_{t-1}} \left(\hat{\varepsilon}_{im}\right) \tag{4}$$

The period M_{t-1} includes all months from the previous four quarters, chosen to provide a reasonable timeframe to observe variations in income while remaining relatively brief to capture potential dynamic changes in income uncertainty that may influence donation and insurance behavior. The magnitude of income uncertainty is consistent with the literature.[15] Results are consistent using alternative periods M_{t-1} of three or two quarters.

Our approach to calculating income uncertainty using recent realized volatility aligns with Di Maggio et al. (2022), who measure firm-level uncertainty through realized volatility of abnormal returns, and with Meghir and Pistaferri (2004), who show that past volatility in unpredicted labor income significantly predicts future income uncertainty. As detailed in Section 3.5, our dataset reflects this same pattern.

3.3 Empirical Results

We empirically examine how income uncertainty predicts donations. These results provide insights regarding the model predictions from spiritual insurance channel. To further explore this channel, we present results on religious versus secular donations, donations following negative income uncertainty and health shocks, and the association between donations and insurance purchasing.

[15] Ganong et al. (2020) report standard deviations of monthly transitory labor income shocks of 0.36 (SIPP) and 0.30 (Chase Bank data). Our sample mean of $\hat{\sigma}_{i,t-1}$ is 0.42, slightly larger but of similar magnitude. Sources of this uncertainty include unpredicted changes in bonuses, wages, and commissions. The sample standard deviation of $\hat{\sigma}_{i,t-1}$ is 0.17, indicating variations in income uncertainty experienced across and within individuals over time. To isolate external variations, we use firm-level leave-one-out average income uncertainty at each point in time as an instrument for its individual-level counterpart, while controlling for individual fixed effects to ensure we use within-person variations.

3.3.1 The Relationship between Uncertainty and Donations

We examine whether individual-level income uncertainty predicts donations consistent with spiritual insurance. Our specification uses within-person variation, tracking changes in realized income uncertainty over time for each individual:

$$\text{donation}_{i,t+1} = \beta_1 \hat{\sigma}_{i,t} + \boldsymbol{X}'_{i,t}\gamma + \mu_t + \lambda_i + \varepsilon_{i,t} \tag{5}$$

The dependent variable $\text{donation}_{i,t+1}$ is either donation incidence (linear probability model) or amount donated in quarter $t+1$. The main independent variable $\hat{\sigma}_{i,t}$ is realized income uncertainty experienced by individual i recently before quarter $t+1$. For ease of interpretation, we standardize $\hat{\sigma}_{i,t}$ to have mean zero and standard deviation one, so β_1 represents the effect of a one-standard-deviation increase in income uncertainty. Controls $\boldsymbol{X}_{i,t}$ include log payroll income, log financial wealth, age, age squared, education, occupation, marital status, and dependents. Continuous control variables are likewise standardized. μ_t and λ_i are time and individual fixed effects. Standard errors are clustered at the individual level to account for potential correlation in regression residuals within individuals.

Our specification improves upon cross-sectional analyses, which often face difficulties to distinguish income uncertainty effects from unobserved individual characteristics. By using within-person variation and individual fixed effects, we control for time-invariant characteristics such as job risk preferences and charitable attitudes. Moreover, using past income uncertainty to predict future donations reduces the risk of simultaneity bias or reverse causality.

Panel A of Table 2 presents estimates of Equation (5) for the predictive relationship between income uncertainty up to quarter t and donation probability in quarter $t+1$. Columns (1)-(3) show OLS estimates with individual and quarter fixed effects (column 1), additional controls (column 2), and city-by-quarter fixed effects (column 3). The income uncertainty coefficient is stable across specifications. Because the income uncertainty variable is already standardized (mean zero, standard deviation one), a one standard deviation increase in income uncertainty predicts a 48% higher donation probability in the next quarter (significant at 1%). Given the average donation of $97.1, this represents an economically meaningful response.[16]

Panel B of Table 2 presents the estimates for the donation amount. Similarly, the standardized coefficient estimate shows that a one standard deviation increase in income uncertainty predicts a 37% increase in unconditional donation amounts (also significant at 1%). Together, Panels A and B indicate that the increase in donations following heightened income uncertainty primarily arises from the extensive margin—an increased likelihood to donate.[17]

[Table 2 here]

Figure A.5 in the Online Appendix presents heterogeneity analysis by age, gender, and marital status. A one standard deviation increase in income uncertainty predicts donation increases of 53%, 41%, and 26% for young, middle-aged, and senior groups, respectively; 39% for males versus 36% for females; and 37% for singles versus 38% for married individuals. Subgroup differences are not statistically significant, and income uncertainty consistently predicts higher donations across all demographic categories.

The residual payroll income fluctuations that we use to measure income uncertainty arise from unpredicted changes in bonuses, wages, and commissions. The estimation exploits within-individual variation in the volatility of these fluctuations over time, reflecting donation behavior following periods of high versus low income uncertainty for the same individual.

The interpretation of estimates from Equation (5) could be influenced by two po-

[16]Control coefficients are in Online Appendix Table A.2. Results are robust to alternative specifications: shorter periods for M_{t-1} (three or two quarters) and individual-month aggregation (Online Appendix Table A.3).

[17]Since donation probability increases by 48%, this implies a modest decrease in the conditional donation amount of approximately -7.4% ($(1+0.37)/(1+0.48)-1$). When uncertainty shocks enhance the perceived spiritual-insurance benefits of charitable giving, they lower the participation threshold, drawing in new donors. These newly motivated donors might be financially less capable or simply have weaker altruistic commitment relative to existing donors. Therefore, they consequently contribute smaller amounts.

tential issues. First, the income uncertainty variable could contain some measurement error, as income uncertainty is not observed perfectly. Second, the income uncertainty variable could potentially conflate external income risk with an individual's labor supply decisions.

For the narrow purpose of isolating variations in income uncertainty not solely attributed to individual labor supply and addressing measurement error, we employ firm-level leave-one-out average income uncertainty as an instrument for individual-level income uncertainty. The leave-one-out approach excludes the individual's own income to help isolate external income uncertainty shocks from individual labor supply choices. We focus on firms with ten or more employees to enhance instrument relevance, as larger firms provide more stable and precise measures of firm-level income uncertainty. Individual fixed effects control for cross-sectional differences, such as religious individuals selecting firms with different risk profiles. By relying on firm-level changes external to the individual, this instrument exploits variations in income uncertainty driven by firm dynamics, which helps reduce potential threats to the exclusion restriction.

Columns (4)-(6) of Table 2 show instrumental variable estimates confirming that income uncertainty predicts higher donations. The first-stage coefficient, which connects individual-level income uncertainty to firm-level average income uncertainty, is 0.56 (reported in Online Appendix Table A.2), with an F statistic exceeding 300, well above conventional thresholds. Column (6) of Table 2 shows the standardized coefficient estimates that a one standard deviation increase in income uncertainty predicts a 130% increase in donation likelihood and a 150% increase in donation amount (both significant at 1%). These results confirm that the increase in donations primarily arises from the extensive margin. The IV estimates exceed OLS estimates, consistent with addressing measurement error.[18]

The positive relationship between income uncertainty and donations in both OLS and IV estimates is consistent with Proposition 1, which assumes a strong spiritual in-

[18]Winsorizing income uncertainty also increases OLS estimates, consistent with measurement error.

surance motive. In contrast, Lemma 1 predicts that without spiritual insurance, higher uncertainty would reduce donations. Our results support the spiritual insurance interpretation.

We also evaluate whether the model with a spiritual insurance motive can quantitatively generate the empirical pattern. Our approach is analogous to the regression analysis: we increase income uncertainty by one standard deviation (by adjusting the value of D) and compute the resulting optimal donation increase (details in Online Appendix Sections A.3 and A.4). The IV estimate's 95% confidence interval (38–262 percentage points) is consistent with a coefficient of relative risk aversion of 4 (Barsky et al., 1997) and spiritual insurance reducing the bad state probability by 6–15%. Alternative combinations could also rationalize the estimate's confidence interval, including lower RRA (e.g., 3) with 5–20% reduction, or higher RRA with narrower ranges (Figure A.2). These parameter ranges demonstrate that the model can quantitatively match the observed donation responses under plausible assumptions about risk aversion and the strength of spiritual insurance beliefs.

We summarize our first main empirical finding regarding the predictive relationship between income uncertainty and donations as follows:

Finding 1 *Higher income uncertainty positively predicts more donations, consistent with the prediction of the model with a strong spiritual insurance channel.*

3.3.2 Donation and Spiritual Insurance

While Finding 1 suggests a potential influence of spiritual insurance on how individuals respond to income uncertainty, several questions remain. First, do religious donations show stronger patterns? Second, do donations increase more for negative uncertainty? Third, do donations negatively associate with insurance purchasing? Our dataset allows us to examine these further questions and distinguish the predictions of the spiritual insurance model.

Donating for Blessings: Religious and Secular Destinations

To explore the role of spirituality in the spiritual insurance mechanism, we categorize donations into religious donations (to foundations connected with a religion or spiritual tradition) and secular donations (to secular foundations). Taiwan's 2003 Survey on Social Development Trends provides context for donation motivations. The survey asked donors about their primary reason for religious or secular donations among five options: supporting the organization's mission, giving back to society, building up charitable deeds and seeking blessings, being influenced by others, and being persuaded by fundraisers.

[Figure 1 here]

Figure 1 shows that "seeking blessings" is the most common motivation for religious donations (56% of donors), suggesting many view contributions as potentially leading to divine blessings. For secular donations, 22% cited "seeking blessings." The 2021 APA-Taiwan survey found a similar 22% for secular charities, suggesting stable attitudes over time.

Given the higher "seeking blessing" motivation for religious donations, we hypothesize that spiritual insurance predictions may be more prominent for these donations. We re-estimate Equation (5) separately for each donation type. Columns (1)-(2) of Table 3 follow the specification of column (3) of Table 2 but differentiate between religious and secular donations. Full control coefficients are reported in Online Appendix Table A.4.

[Table 3 here]

OLS results in Table 3 show income uncertainty positively predicts both donation types, with a more pronounced effect observed for religious donations. For donation likelihood (Panel A), the standardized coefficient estimates suggest that a one standard deviation increase in income uncertainty predicts a 53% increase in religious donation likelihood versus 39% for secular donations. The absolute magnitude of the religious donation likelihood estimate is 96% larger (significantly different at 1%). For donation amounts (Panel B), the standardized coefficient estimates suggest that a one standard deviation increase in income uncertainty predicts a 38% increase in religious donation amount versus 36% for secular donations. The absolute magnitude of religious donation amount estimate is 52% larger (significantly different at 5%). Consistent with overall donations, increases in both types of donations and the differential strength of the religious donation response primarily arise from the extensive margin. In general, religious donations exhibit greater increase after experiencing heightened income uncertainty.[19][20]

Columns (5)-(6) of Table 3 show similar patterns in IV estimates. The standardized coefficient estimates suggest that a one standard deviation increase in income uncertainty predicts a 138% increase in religious donation likelihood, which is 92% larger than that for secular donations. The unconditional amount of religious donations increases by 167%, which is 89% larger than that for secular donations. Together, the OLS and IV results are consistent with the higher share of donors reporting "seeking blessings" motivation for religious donations (Figure 1).

Negative Income Uncertainty Shock and Positive Income Uncertainty Shock

American psychologist William James suggested a utilitarian perspective in which religion might improve well-being by offering relief from certain "evils" in the world (James, 1902). Is the predictive relationship we find stronger for downside risk (e.g., Ang, Chen, and Xing, 2006)? To better understand this potential distinction, we decompose the income uncertainty measure into positive and negative income uncertainty.

We employ the semi-deviation method, a commonly used approach for measuring downside risk (e.g., Segal, Shaliastovich, and Yaron, 2015), to decompose income uncertainty into positive and negative components, then explore how each predicts religious

[19] We address multiple hypothesis testing following Romano and Wolf (2005) (Online Appendix Section A.6 and Table A.5); the difference between religious and secular donations is robust.

[20] Most of the religious donations in our dataset went to evangelical foundations, which are primarily responsible for our results. Buddhist foundations adopted online donations later, resulting in smaller shares. Nevertheless, a one standard deviation increase in income uncertainty predicts a 58% increase in Buddhist donation likelihood, comparable to evangelical donations. Since Buddhist congregations have looser affiliations less conducive to informal risk-sharing, this further supports the spiritual insurance interpretation over local mutual insurance.

and secular donations.[21] We control for the first moment of income during the same period, so results do not merely reflect income levels; an increase in $\hat{\sigma}^{\text{pos}}$ ($\hat{\sigma}^{\text{neg}}$) means positive (negative) income changes are becoming more uncertain. Note that spiritual insurance in our model is two-sided: it may protect against adverse outcomes (affecting subjective expected outcomes of negative uncertainty) and enhance prospects for favorable outcomes (affecting subjective expected outcomes of positive uncertainty).

Columns (3)-(4) of Table 3 present OLS estimates. Both negative and positive income uncertainty predict increases in religious and secular donations, with negative uncertainty showing consistently larger point estimates. The standardized coefficient estimates suggest that a one standard deviation increase in negative income uncertainty predicts a 30% increase in religious donation likelihood, compared to 21% for positive uncertainty.[22] This difference in predicting donation likelihood is marginally significant at the 10% level ($p = 0.081$), though not after multiple hypothesis testing adjustment ($p = 0.121$); the difference in predicting donation amount is not significant (see Online Appendix Table A.6). The results suggest spiritual insurance responds to uncertainty broadly, with downside uncertainty naturally activating divine protection motives and positive uncertainty potentially reflecting a "praying for success" mechanism, both as in our model. These possible considerations make spiritual insurance more beneficial both in times of heightened downside uncertainty or upside uncertainty.

Columns (7) and (8) of Table 3 show similar patterns in IV estimates using firm-level average positive and negative income uncertainty as instrument for individual-level counterparts. In these instrumental variable regressions, the only significant estimate at the 10% level is the estimate for negative income uncertainty and religious dona-

[21]Positive and negative income uncertainties are calculated based on whether an individual's demeaned residual income in a given month is above or below zero:

$$\hat{\sigma}^{\text{pos}}_{i,\{t-1,\ldots,t-T\}} = \sqrt{\frac{1}{T-1}\sum_{s=t-T}^{t-1} \mathbb{I}\left\{\Delta\hat{\varepsilon}_{is} \geq 0\right\} \Delta\hat{\varepsilon}_{is}{}^2}; \quad \hat{\sigma}^{\text{neg}}_{i,\{t-1,\ldots,t-T\}} = \sqrt{\frac{1}{T-1}\sum_{s=t-T}^{t-1} \mathbb{I}\left\{\Delta\hat{\varepsilon}_{is} < 0\right\} \Delta\hat{\varepsilon}_{is}{}^2},$$

where $\Delta\hat{\varepsilon}_{is}$ is the demeaned residual income for individual i in month s ($\Delta\hat{\varepsilon}_{is} \equiv \hat{\varepsilon}_{is} - \frac{\sum_{\tau=t-T}^{t-1}\hat{\varepsilon}_{i\tau}}{T}$).

[22]Non-normalized coefficients would show an even larger coefficient for negative uncertainty, as one standard deviation in $\hat{\sigma}^{\text{neg}}$ (0.11) is smaller in absolute units than in $\hat{\sigma}^{\text{pos}}$ (0.13).

tions. The standardized instrumental variable coefficient estimates suggest that a one standard deviation increase in negative income uncertainty predicts a 119% increase in the likelihood of making religious donations and a 151% increase in the unconditional amount of religious donations; for positive income uncertainty, a 40% increase in the likelihood of making religious donations and a 43% increase in the unconditional amount of religious donations.

Health Shock as a Negative Shock

Besides income uncertainty, disease is another adverse shock often associated with spiritual insurance. In a meta-analysis on spirituality and health in the Lancet, Sloan, Bagiella, and Powell (1999) reports that 79% of US adults believed spiritual faith can help people recover from disease. We explore whether spiritual insurance may be relevant in response to health shocks that represent adverse realizations of health risk. Disease can significantly affect household finances through not only medical expenditures but also a potential increase in future income uncertainty.

Under the spiritual insurance hypothesis, health shocks may counterintuitively increase donations, as households facing adversity seek blessings and healing. We investigate how health shocks predict donation behavior. We also consider health shocks as potentially exogenous, providing an additional test of the spiritual insurance motive.

We define a health shock as medical expenditures in the past quarter exceeding the sample's positive median.[23] We estimate:

$$\text{donation}_{i,t+1} = \beta_1 \text{health shock}_{i,t} + \boldsymbol{X}'_{i,t}\gamma + \mu_t + \lambda_i + \varepsilon_{i,t} \tag{6}$$

where health shock$_{i,t}$ is either a dummy for at least one health shock or, for robustness, the standardized amount of above-median medical expenditures. Other variables are defined as in Equation (5).

[23]We exclude cosmetic surgery transactions to ensure expenditures represent negative shocks rather than spending power. Results are robust to varying the health shock window to two quarters or adjusting the donation window to one month.

[Table 4 here]

Table 4 presents results on health shocks. Full control coefficients are reported in Online Appendix Table A.7. Health shocks in the preceding quarter predict higher donation likelihood in the following quarter. Experiencing at least one health shock is associated with a 270% increase in donation likelihood (column 1), while the standardized coefficient estimate suggests that a one standard deviation increase in health shock spending is associated with a 52% increase (column 4). Similarly, health shocks predict 146% and 31% increases in unconditional donation amounts, respectively. These findings suggest health shocks increase donations primarily through the extensive margin.

The remaining columns of Table 4 examine religious versus secular donations. Health shocks significantly predict religious donations: at least one health shock is associated with a 354% increase in donation likelihood and a 236% increase in donation amount (both significant at 1%). For secular donations, health shocks predict a 139% increase in likelihood but no significant increase in amount (p=0.377). Medical expenditure amounts show similar patterns: robust increases for religious donations but smaller, less significant effects for secular donations.

Put together, the observed positive relationships between income uncertainty or health shocks and donations are consistent with the idea that spiritual insurance, particularly through religious donations, may serve as a response to uncertainty or adverse events. We summarize our second main finding as follows:

Finding 2 *Income uncertainty predicts higher donations, particularly for religious donations. Moreover, the increase in religious donations is consistently pronounced after experiencing negative income uncertainty. Health shock, another prominent negative shock, also predicts more religious donations.*

3.3.3 The Negative Association between Spiritual Insurance and Insurance Purchasing

The extended model's prediction in Section 2 motivates our examination of the relationship between donations and insurance purchases. If there is a possibility that a spiritual insurance motive influences donations and is sufficiently strong, Proposition A.1 suggests that we may observe a negative contemporaneous association between donation behavior and insurance purchasing. We test whether individuals reduce insurance purchases when donating, particularly for religious donations, using:

$$\begin{aligned} \text{insurance}_{i,t+1} = & a_1 \cdot \mathbb{I}\left\{\text{donation}_{i,t+1} > 0\right\} + a_2 \cdot \hat{\sigma}_{i,t} \\ & + \boldsymbol{X}'_{i,t}\gamma + \mu_t + \lambda_i + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where $\text{insurance}_{i,t+1}$ is the amount of insurance individual i purchased in quarter $t+1$, and $\mathbb{I}\left(\text{donation}_{i,t+1} > 0\right)$ is a dummy variable that indicates at least one donation in that quarter. The dummy variable approach allows us to focus on the extensive margin of donations that informs our primary results; however, it is not essential—we also replace the donation dummy with donation amount and present the results.

We control for income uncertainty ($\hat{\sigma}_{i,t}$) since it may influence both insurance purchases (Guiso and Jappelli, 1998) and donations. Other control variables such as income level, financial wealth are defined as before. Individual fixed effects (λ_i) account for time-invariant characteristics affecting both behaviors. The coefficient a_1 captures the within-person difference in insurance purchases between quarters when the individual donates versus does not donate.

We estimate Equation (7) for all donations, then separately for religious and secular donations. Table 5 presents the results.

[Table 5 here]

Panel A of Table 5 presents the donation dummy results. Full control coefficients are reported in Online Appendix Table A.8. Column (1) shows that, using within-person variations, donating at least once in a quarter is associated with a 71.03 USD decrease in insurance purchases (approximately one-third of the sample mean), significant at the 1% level.

Panel B presents consistent results using donation amounts: each $1 donated is associated with a $3.73 reduction in insurance spending. This negative relationship is consistent with spiritual insurance and insurance products serving as substitutes. The amplified negative relationship indicated by the dollar amounts represents a noteworthy finding.

To contextualize this estimate, we conduct a simulation exercise using our extended model (detailed in Online Appendix A.4, Figure A.4). The model maps the change in insurance expenditures per $1 donation to various parameter combinations. Our empirical estimate of approximately $4 reduction aligns with the model across a broad range of parameters. For example, with a coefficient of relative risk aversion of 4 (Barsky et al., 1997) and a spiritual insurance channel strength where the average donation reduces the perceived adverse state probability by approximately one-fifth, the model generates similar predictions. We assess this parameter combination to be plausible.

Religious donations show a more pronounced negative association with insurance purchases. Column (2) of Panel A indicates that donating to religious foundations is associated with an 89.95 USD reduction in insurance purchases (42% of average quarterly spending). Panel B shows each $1 of religious donation is associated with a $5.25 reduction in insurance spending. In contrast, secular donations (column 3) show smaller, statistically insignificant effects.

We are also interested in how donations may influence the relationship between income uncertainty and insurance purchases. We estimate:

$$
\begin{aligned}
\text{insurance}_{i,t+1} = & a_1 \cdot \mathbb{I}\{\text{donation}_{i,t+1} > 0\} + a_2 \cdot \hat{\sigma}_{i,t} \\
& + a_3 \cdot \mathbb{I}\{\text{donation}_{i,t+1} > 0\} \cdot \hat{\sigma}_{i,t} \\
& + \boldsymbol{X}'_{i,t}\gamma + \mu_t + \lambda_i + \varepsilon_{i,t}
\end{aligned}
\tag{8}
$$

The coefficient a_3 captures whether the sensitivity of insurance purchases to income uncertainty differs when individuals donate versus do not donate. Other variables are defined as before.

Column (4) of Table 5 presents the estimation results of Equation (8). As a pretest, we observe a positive a_2: a one standard deviation increase in income uncertainty is associated with a statistically and economically significant increase of 101.53 USD in insurance purchases when individuals do not donate. This positive a_2 in normal times reflects the precautionary motive: when prudent individuals face greater uninsurable background risk (higher income uncertainty), they increase demand for insurance against other controllable risks (Guiso and Jappelli, 1998).[24] However, we observe a large, negative, and significant a_3 of 96.68 USD. When individuals do donate, their insurance purchases may no longer be predicted by income uncertainty; the same increase leads to a statistically and economically insignificant increase of 4.85 USD ($a_2 + a_3 = 101.53 - 96.68 = 4.85$).[25]

Columns (5) and (6) show this sensitivity change is more clearly observed for religious donations. For religious donations, the positive relationship between income uncertainty and insurance purchases is effectively offset (a_3 = 119.33 USD, significant at 5%). For secular donations, the change is smaller and insignificant (a_3 = 64.78 USD). These results indicate that donations, particularly religious donations, are significantly linked to changes in how individuals respond to income uncertainty when making insurance decisions.

[24]Our specification includes both $\hat{\sigma}_{i,t}$ and income level in $\boldsymbol{X}_{i,t}$. Consistent with the income effect, higher income level is associated with increased insurance purchase (Online Appendix Table A.8). This is distinct from the positive precautionary motive (a_2): holding income level fixed, rising income uncertainty also predicts more insurance purchases. We observe in untabulated results that income uncertainty is also associated with reduced discretionary spending, further aligning with the precautionary motive.

[25]We extend this analysis to examine how the sensitivity change varies with the sign of income uncertainty shocks (Online Appendix Table A.9). As expected, among donors, the sensitivity change is statistically significant for downside uncertainty but insignificant for upside uncertainty. Formal tests comparing these differences, as have been reported in Online Appendix Table A.6, confirm that the sensitivity change is significantly stronger for downside uncertainty even after MHT adjustment (10% level). This asymmetry aligns with the interpretation that downside uncertainty more directly activates the divine protection aspect of spiritual insurance motives, leading to stronger substitution away from formal insurance.

Could financial constraints (e.g., Yao and Zhang, 2005) explain these patterns? While the differing estimates between religious and secular donations suggest that financial constraints may not be the primary factor, we further examine individuals unlikely to be financially constrained—those whose monthly income consistently exceeds total expenditures, including consumption and the higher of their actual maximum or sample average monthly spending on insurance and donations. Results remain similar among those unlikely to be financially constrained (Online Appendix Table A.10), indicating that the negative association between donations, particularly religious donations, and insurance purchases is not purely explained by financial constraints.

To rule out statistical chance, we conduct a placebo test in which we replace the donation dummy with a dummy variable indicating high consumption spending, using several specifications that differ in the thresholds for defining high consumption spending. We find no negative relationships between these placebo high-spending indicators and insurance purchases (see Online Appendix Table A.11). This confirms that the observed negative association is specific to donations rather than a general artifact of increased spending.

To sharpen the temporal ordering, we examine whether donations predict insurance reduction at the monthly frequency. Intuitively, if religious giving causally crowds out insurance, donations made this month should predict *lower* insurance outcomes next month; simultaneity or reverse causality would not generate this one-step-ahead pattern. Table 6 shows the results estimating whether donations in month t predict lower insurance purchases/expenditures in months $t+1$ or $t+2$, at the highest frequency the data allow, using the same sample and control variables used in Table 5. Religious donations in month t significantly predict a \$17.26 decline in total insurance spending in month $t+1$ (23% of the \$74.27 monthly mean) and a 2.0 percentage point drop in purchase probability (19% of the 10.7 percentage point baseline); both become statistically insignificant in $t+2$, indicating that the effect is concentrated in the immediately following month. The intensive margin coefficient for insurance expenditures in month

$t + 1$ is directionally negative (a $50.28 decline in the intensive margin), but it is statistically insignificant. Secular donations are null at both horizons on all margins. This religious-specific, predictive pattern demonstrates that a reduction in insurance expenditures follows religious donations. This temporal pattern provides suggestive evidence that donation behavior may have a causal effect on insurance expenditures.

[Table 6 here]

To interpret the economic meaning of "reducing insurance expenditure," we decompose the quarterly substitution by prior-purchase status, renewal timing, and margin. Since contract identifiers are unobserved, we construct two transaction-history proxies: a *Prior* indicator for any insurance transaction before quarter t, and *Prior*$_{k4}$ for prior purchasers whose most recent transaction was exactly four quarters earlier (proxy for annual renewal). Table 7 reports this decomposition.

On average, with observed religious donations, prior purchasers (Panel A) show an extensive margin in insurance expenditure that is not significantly reduced and an intensive margin that significantly falls, but this average result masks the sharper split by likely annual renewal. Within prior purchasers, the effect sharply concentrates at the predicted renewal timing. $Prior_{k4}$ individuals (Panel B), who may have an insurance policy that is up for annual renewal, show significant reductions in insurance expenditure on all three margins: $-\$262$ total; -3.8 percentage point extensive (likely reflects non-renewal); $-\$385$ intensive (likely reflects coverage reduction or switching to a cheaper product).[26] $Prior_{non-k4}$ individuals (Panel C) are uniformly insignificant.[27]

[26]Our data record monthly-aggregated payment flows on purchases of insurance products. The data do not allow us to infer premiums, contract terms, or renewal dates. Thus, the $Prior_{k4}$ indicator—individuals whose most recent insurance transaction was exactly four quarters before the donation quarter—is a proxy for rather than a contract-observed annual-renewal window. To the extent that multi-year policies or policies billed in monthly installments spread the true renewal event across several quarters, the Prior$_{k4}$ concentration we document is a *lower bound* on the true renewal-window concentration of the donation-insurance substitution.

[27]Online Appendix Figure A.6 confirms this with a finer cut by re-estimating the effect at each single lag $k \in \{-6, \ldots, -1\}$ separately, where k is the relative timing in quarters between the individual's most recent insurance transaction and the donation quarter (so $k = -4$ means the most recent insurance transaction occurred four quarters before the donation, consistent with an annual-renewal window opening in the donation quarter). The religious panel shows a negative spike in insurance expenditure at $k = -4$

Individuals without prior observed insurance purchases (Panel D) show no significant dollar effect but a statistically significant 0.83 percentage point reduction in the purchase probability (15% of the 5.37 percentage point baseline). Secular donations are null throughout. The observed lower insurance expenditure with religious donation thus operates through distinct margins at both edges of the insurance experience distribution: among experienced buyers at the annual-renewal decision it shrinks coverage through likely non-renewal and coverage downgrade, and among individuals without prior observed insurance purchases it deters first-time entry.

[Table 7 here]

We further examine whether the lower observed insurance spending reflects delayed purchases, temporary lapse, or permanent reduction in coverage. We estimate a separate regression for each quarter $h \in \{-2, \ldots, +3\}$ relative to the donation quarter, where the dependent variable is insurance expenditure in quarter h and the independent variable is the quarter-0 donation dummy. Online Appendix Figure A.7 traces the insurance purchase dynamics for the whole sample, and Online Appendix Figure A.8 for the Prior$_{k4}$ sample (for whom the donation quarter is also the renewal quarter).[28] Importantly, if the $h = 0$ reduction reflects a delayed purchase or temporary lapse, we should observe significant positive coefficients (a make-up purchase) at $h = +1, +2$, or $+3$; if the reduction is permanent, those coefficients should remain near zero. In the quarters after the renewal window, no coefficient is significantly positive: observed insurance spending estimates remain negative and insignificant through $h = +2$, with a small positive and insignificant estimate at $h = +3$. The absence of any significant positive rebound in the post-event quarters suggests that the renewal-window substitution is consistent with permanent reduction in coverage rather than delayed purchase or temporary lapse.

We also examine heterogeneity in substitution patterns across demographic groups

on all margins, with flat and insignificant estimates at $k = -3$ and $k = -5$; the concentration is specific to the annual-renewal quarter.

[28]Pre-trend coefficients at $h = -2$ and $h = -1$ are small and insignificant in both figures, ruling out reverse causality.

(age, gender, marital status). Results, presented in Online Appendix Figure A.9, show qualitatively similar reductions across all groups, with modest (statistically insignificant) differences suggesting that younger, male, and single individuals (possibly financially less experienced or more over-confident) may substitute slightly more aggressively. This pattern indicates that the donation–insurance substitution exists broadly across demographic segments.

The negative association between donations and insurance purchases, particularly for religious donations, suggests additional empirical patterns, time-ordered and persistent, consistent with a spiritual insurance channel. We summarize these findings as follows:

Finding 3 *Conditional on donating, particularly to foundations connected with a religion or spiritual tradition, people (a) buy less insurance, and (b) their insurance spending no longer responds to income uncertainty, even among those unlikely to be financially constrained.*

3.4 Examining Alternative Explanations

We have discussed early on that Finding 1, that income uncertainty predicts higher donations, is difficult to explain without a spiritual insurance channel. Having reported Findings 2 and 3, we now examine whether these findings help differentiate spiritual insurance from alternative explanations.

Mutual Insurance

One alternative explanation is that religious donations function as informal insurance: donating strengthens community ties (e.g., within a church), which provide reciprocal support during future adverse shocks. Literature provided evidence on this mutual insurance mechanism, as households donating to religious organizations better insure their consumption (Dehejia, DeLeire, and Luttmer, 2007). However, this channel's applicability here is questionable. Donations in our dataset go to broad-based foundations (not local churches nor central offices of local churches) that by law must assist unspecified individuals (not the donor) in disadvantaged groups (e.g., children in poverty, global disaster relief) outside donors' social circles, often beyond the local economy. Thus, the chance of significant mutual insurance effects is reduced.

We nonetheless test this by replicating Dehejia, DeLeire, and Luttmer (2007)'s specification: examining whether donations correlate with increased consumption insurance, measured by reduced pass-through of income growth to consumption growth. Online Appendix Table A.12 shows no significant improvement in consumption insurance from either religious or secular donations. This suggests that donations in our context are unlikely to function through informal consumption insurance within the community.

Increased Altruism

Another possible explanation is increased altruism: experiencing income uncertainty or health shocks may heighten sympathy toward those in need, which could influence their altruistic behavior (Chen and Zhong, 2025). While Finding 1 may initially appear consistent with increased altruism, if altruism were the primary driver, one would expect similar estimates for both religious and secular donations. However, Finding 2, the more pronounced sensitivity of religious donations to income uncertainty and health shocks, suggests some inconsistency with a straightforward increase in altruism.

Alternatively, one might speculate that religious individuals' altruism is more responsive to personal experiences. This could produce the asymmetry in Finding 2. While plausible, neither a simple increase in altruism nor an asymmetric increase in altruism among religious donors sufficiently account for Finding 3, the negative association between donations and insurance purchases, even among those unlikely to be financially constrained.

We illustrate this limitation of increased altruism to explain Finding 3 using an extended model with increased altruism instead of spiritual insurance (Online Appendix A.5). While sufficiently strong increased altruism can raise donations with income uncertainty, it does not reproduce a negative association between donations and insurance. Intuitively, giving more leaves fewer resources, increasing the marginal benefit of and thus the need for insurance. By contrast, spiritual insurance can match all three findings, including Finding 3: if donations reduce the subjective likelihood of adverse income states, they lessen the perceived need for insurance (Proposition A.1). In sum, while altruism alone can raise giving under uncertainty, it cannot explain why donation is negatively related to insurance purchases.

Income Seasonality

Income uncertainty in our sample may arise from performance-based compensation, fluctuations in commissions, wage raises and wage cuts, as well as bonuses. To help ensure our results are not influenced by the seasonality of these income fluctuations, we have included quarter-of-the-year fixed effects in all our regressions.

As an additional robustness check (Online Appendix Table A.13), we exclude payroll observations from January, February, and July (months associated with annual bonus payouts) from our income uncertainty computation. Income uncertainty then primarily reflects commissions and within-year performance-based pay. Our findings remain consistent, indicating that our results are not solely attributable to income seasonality.

Tax Considerations

Income uncertainty shocks may correlate with the price of giving (one minus the marginal tax rate). We impute marginal tax rates using two methods: (1) annualizing monthly payroll income; (2) using ex-post annual income when available, otherwise extrapolating with seasonality adjustments. Online Appendix Table A.14 shows our results remain consistent when controlling for these imputed marginal tax rates. This reinforces the robustness of our findings.

In sum, the analysis in this section suggests that our findings on the relationship between income uncertainty, donations, and insurance purchasing are unlikely to be solely attributed to mutual insurance, increased altruism, income seasonality, or tax considerations. Instead, these findings appear to uniquely highlight the role of the spiritual insurance channel.

3.5 Discussion: Are Future Risks Materially Reduced?

A post-hoc question is whether donations materially reduce future income uncertainty. If donations provide psychological comfort, anticipating a better future may reduce stress, improve work performance, and reduce future income uncertainty, creating a "self-fulfilling prophecy." While this possibility does not invoke supernatural forces, it can still yield similar outcomes.

To more directly explore this question, we regress second-year income uncertainty on a first-year donation indicator, first-year income uncertainty, and their interaction. The first year spans July 2013 to June 2014, and the second year spans July 2014 to June 2015, corresponding to the first and second halves of our sample period. The coefficient on the donation indicator is our primary coefficient of interest. The interaction between first-year income uncertainty and the donation indicator also capture whether donations made during periods of higher uncertainty have differential effects. We estimate this regression separately for total donations, religious donations, and secular donations. We also consider donation amounts instead of the donation indicator. Results are presented in Table 8.

[Table 8 here]

The results in Table 8 first indicate that first-year income uncertainty significantly and positively forecasts second-year income uncertainty. This pattern is consistent with Meghir and Pistaferri (2004) and provides assurance regarding our approach using an income uncertainty measure based on realized volatility. Full control coefficients are reported in Online Appendix Table A.15.

The results in Table 8 then suggest that first-year donations, whether the act or the amount, do not significantly predict second-year income uncertainty. Furthermore, considering religious and secular donations separately, neither predicts a reduction in future uncertainty. Additionally, donations made during periods of higher income uncertainty also did not predict future uncertainty.

Collectively, we do not find significant evidence that donations have a material effect on future income uncertainty, suggesting that the anticipated benefits associated with spiritual insurance may be more psychological than material in nature. Consistent with this view, donors and non-donors also exhibit similar probabilities of subsequent health shocks (see Online Appendix Table A.16), implying no observable improvement in risk avoidance. Considering the observed reduction in insurance purchases, such spiritual insurance behaviors could potentially point to adverse financial consequences in expectation. However, our findings do not rule out, and may even be consistent with belief-based utility models (e.g., Caplin and Leahy, 2001; Brunnermeier and Parker, 2005). They may align in the sense that donations, particularly religious donations, can increase psychological utility for some individuals, even though these behaviors may not improve and could even reduce material well-being once potential financial consequences are considered.

4. The Field Experiment on Spiritual Insurance Narratives

To directly examine how spiritual insurance narratives affect donation behavior, specifically the idea of good deeds yielding divine favor, we analyze a field experiment that utilizes such narratives by Platform X, a leading charitable crowdfunding platform in mainland China and globally.

By 2023, Platform X primarily aided low-income patients with severe illnesses, involving hundreds of millions of users and billions in donations (about 10% of total charitable giving in mainland China). Patients submit verified medical and financial details to start campaigns, which are then posted for donors with full information, allowing informed giving. This platform operates differently from traditional charity organizations such as the American Red Cross, where visitors are typically regular donors actively seeking giving opportunities. On Platform X, donation links circulate primarily through WeChat Moments, a feature similar to Facebook's News Feed, where users see posts shared by their social contacts. In our sample, the vast majority of visitors (98.7 %) arrive passively and incidentally through their social networks rather than as active charity seekers. Given that WeChat is China's largest social media platform with more than 1.3 billion active users, these links reach a very broad audience.[29] As a result, donation requests are encountered by members of the general population who typically do not pay much attention to charitable giving and see such appeals only passively and occasionally.

4.1 Experimental Design

This experiment tested whether a spiritual insurance narrative could influence donation behavior on Platform X. Treated users saw a message below the donation button: "Accumulate good spiritual connections to receive karmic blessings".[30] This subtle prompt was designed to emphasize the notion that good deeds bring divine favor, as a form of spiritual insurance against future uncertainty, distinct from social or mutual insurance. Figure 2 shows the interface. Control users saw the standard donation page without the message.

[Figure 2 here]

During the 19-day experimental period (July 28 to August 15, 2022), we cannot observe how many individuals were actually exposed to the donation link. What we do observe is that approximately four million users clicked 187 thousand links and entered

[29] WeChat reported over 1.3 billion monthly active users as of Q3 2022; see Tencent's official product statistics at https://www.tencent.com/en-us/products/weixin.html.

[30] The treatment message was 'jī shàn yuán dé fú bào" in Mandarin Chinese, an idiom traditionally used to emphasize the spiritual insurance narrative. "Jī" means "to accumulate." "Shàn yuán" combines "virtuous" and "spiritual connections," indicating that through virtuous actions, one accumulates a spiritual connection with divine beings. "Dé" means "to receive." "Fú bào" combines "good fortune" or "luck" with "retribution" or "karmic returns," signifying "karmic returns that protects from bad luck and enhances good fortune."

the donation website. These users were then individually randomized into treatment and control groups.

4.2 Experiment Results

The analysis includes two data sets: donor behavior and fundraiser characteristics (see Online Appendix Table A.17 for variable definitions).[31] Donor data included donation behavior, age, location, the manner in which they learned of each campaign, historical donation activities, and anonymous donation history. Fundraiser data included disease type, campaign details, target amount, patient age, patient gender, and insurance coverage.

Random assignment ensured comparability between groups, as shown by balance tests on 25 covariates (see Online Appendix Table A.18). In terms of donor history, it is important to emphasize that accounting for when each user registered, the average (median) contribution incidence has been only 1.0 (0.4) time per year, and the yearly average (median) donation amount has been $ 4.4 ($ 1.0). For context, the per capita average donation amount to registered nonprofits in mainland China in 2022 was $10.7.[32] Taken together, these statistics indicate that users in our sample are not frequent donors and more likely reflect the characteristics of the general population.[33]

Average Treatment Effects

Our primary interest in the field experiment was to test if the spiritual insurance narrative below the donation button affected donor behavior. Figure 3 shows that while the donation rate was 5.752% for controls, it increased to 5.806% with treatment, a 0.93%

[31]We designed the data analysis plan and submitted it to Platform X, which conducted analysis within the platform. Data remains within Platform X's premises and is not extracted. We only obtained the results of the analysis as requested.

[32]China's Ministry of Civil Affairs reported total donations to registered nonprofits of $15.0 billion (108.5 billion yuan) in 2022 in the *Statistical Bulletin on the Development of Civil Affairs in 2022*, equivalent to $10.7 per capita on average. See http://www.crca.cn/images/20231023-1.pdf.

[33]Most of the campaign patients in our sample were covered by basic health insurance but still faced notable financial burdens, particularly in relation to cancer diagnoses. The average campaign target was approximately 42,000 USD. Petitioning patients typically wrote long descriptions (848 characters) and uploaded multiple photos (over 7) to appeal others to donate.

relative rise, despite the intervention's minimal presence (just 1/60th of the screen). For context, this effect is about one-quarter the size of the social pressure effect found by Chan et al. (2024), who manipulated the donation screen more prominently (1/10th of the screen, center placement) by highlighting peer behavior. Our treatment's effect size thus appears significant, particularly given the minimal adjustment to the donation interface. No significant change was observed in donation amounts (the intensive margin), implying the narrative predominantly influenced the likelihood of donation ("doing a good deed"), not the size of gifts ("the magnitude of the good deed").[34]

[Figure 3 here]

Heterogeneous Treatment Effects: Regional Variations in Spiritual Narratives

Cultural differences (Stulz and Williamson, 2003; Guiso, Sapienza, and Zingales, 2006) may shape the impact of spiritual insurance narratives. In regions with greater exposure to beliefs that fate may be influenced by supernatural forces, one might observe larger treatment effects. To assess this, we used the Baidu search index—akin to Google Trends (Shiller, 2017), which tracks keyword search frequency by region. Our analysis used prefectural cities (similar to MSAs) as the geographic unit.

To gauge pre-exposure to spiritual narratives, we used city-level Baidu search volumes for eight keywords that traditionally signify being influenced by a higher power and have substantial web search volume.[35] We collected city-level search indices for each keyword in 2022 and conducted principal component analysis, retaining the first principal component. We then winsorized this first principal component at the 1% and

[34]The point estimate for the conditional donation amount is in fact imprecisely negative (-0.39%). As a result, the unconditional donation amount increased by approximately 0.51%, though this increase is statistically insignificant at the individual level. This experimental response in the conditional donation amount echoes the OLS estimate in our bank transaction data analysis, where we find donation likelihood increased by 48%, unconditional donation amount rose by 37%, but conditional donation amount reduced by 7%. Both are consistent with donor base expansion and a "walking down the demand curve" effect, whereby spiritual cues induce marginal donors with lower giving capacity or weaker altruistic motivation to enter the market, which are also consistent with experimental findings in other non-altruism motives for donations (DellaVigna, List, and Malmendier, 2012).

[35]These keywords were "God of Wealth" (cái shén), "Feng Shui" (fēng shuǐ), "auspicious day of the zodiac" (huáng dào jí rì), "warding off evil spirits" (pì xié), "praying for good luck" (qí fú), "burning incense" (shāo xiāng), "karma" (yīn guǒ), and "I Ching/Book of Changes" (zhōu yì).

99% level and used its z-score. This component reflects the predominant search patterns associated with spiritual narratives across regions.

If the first principal component of the Baidu search indices reflects spiritual narratives and if spiritual insurance influences donations, it should correlate with city-level donation rates. Table 9 Column (1) shows the results of regressing average donations (measured as city total donations on Platform X during the experiment per million residents and z-scored) on this component, while Column (2) adds city-level controls such as per-capita income, public expenditures, and coverage of public programs, all likewise z-scored. The estimates from both columns indicate that this city-level measure of pre-exposure to spiritual narratives is positively correlated with per-capita donations on Platform X: specifically, a one standard deviation increase in pre-exposure to spiritual narratives predicts a 0.33 standard deviation increase in per-capita donations, and this association is statistically significant at the 1% level. Notably, the explanatory power of this spirituality measure is quantitatively comparable to three other variables that also show significant explanatory power (per-capita retail sales, public education expenditure, and the coverage rate of unemployment insurance).

[Table 9 here]

Then, we estimate the relationship between the first principal component of the Baidu search indices, our measure of city-level pre-exposures to spiritual narratives, and heterogeneous treatment effects on donation likelihood in the experiment. This is done by regressing the latter on the former, both winsorized at the 1% and 99% levels and z-scored. Column (3) reports the univariate result, and column (4) includes the same set of city-level controls. The results from both columns indicate a statistically significant positive correlation between pre-exposure to spiritual narratives and treatment responsiveness; specifically, a one standard deviation increase in the spirituality component is associated with a 0.124 (0.174) standard deviation increase in the treatment effect in the univariate (multivariate) specification. These coefficients are statistically significant at the 5% level (p-value $= 0.034$ without controls, 0.011 with controls). Panel

A of Figure 4 visually illustrates this relationship, suggesting that regions with stronger spiritual beliefs may see more pronounced donation likelihood increases in response to the spiritual insurance narrative experiment.

We also examine whether the treatment effect on the unconditional donation amount varies with city-level pre-exposure to spiritual narratives. As shown in Columns (5) and (6) of Table 9, there is a significant positive treatment effect on the unconditional donation amount in cities with a higher spirituality-related Baidu search index. After including controls, a one-standard-deviation increase in the city-level spirituality index is associated with a 0.121 standard deviation increase in the treatment effect on the unconditional donation amount ($p < 0.10$). Panel B of Figure 4 visualizes this relationship by plotting the city-level treatment effects on the unconditional donation amounts against the spirituality index, revealing a clear upward trend similar to that of the extensive margin. This heterogeneity pattern suggests that while making the spiritual insurance narrative salient generally nudges more people to decide to give, it is in areas where these beliefs are widespread to begin with that the salience of this narrative also influences how much people give.

[Figure 4 here]

Together with our initial findings from the archival data, the experimental results point to a possible link between spiritual insurance and changes in real-world behavior. Specifically, the experiment shows that spiritual insurance narratives, which posit that good deeds can build spiritual connections and result in karmic blessings during future uncertainty, can motivate people to donate.

The consistency between the archival data and field experiment results suggests that the spiritual insurance channel may shape how individuals psychologically respond to risk, especially when they believe that uncertain outcomes could be influenced by a higher power rewarding good deeds. This observation could contribute to a more multidimensional understanding of decision-making under risk and approaches to managing uncertainty.

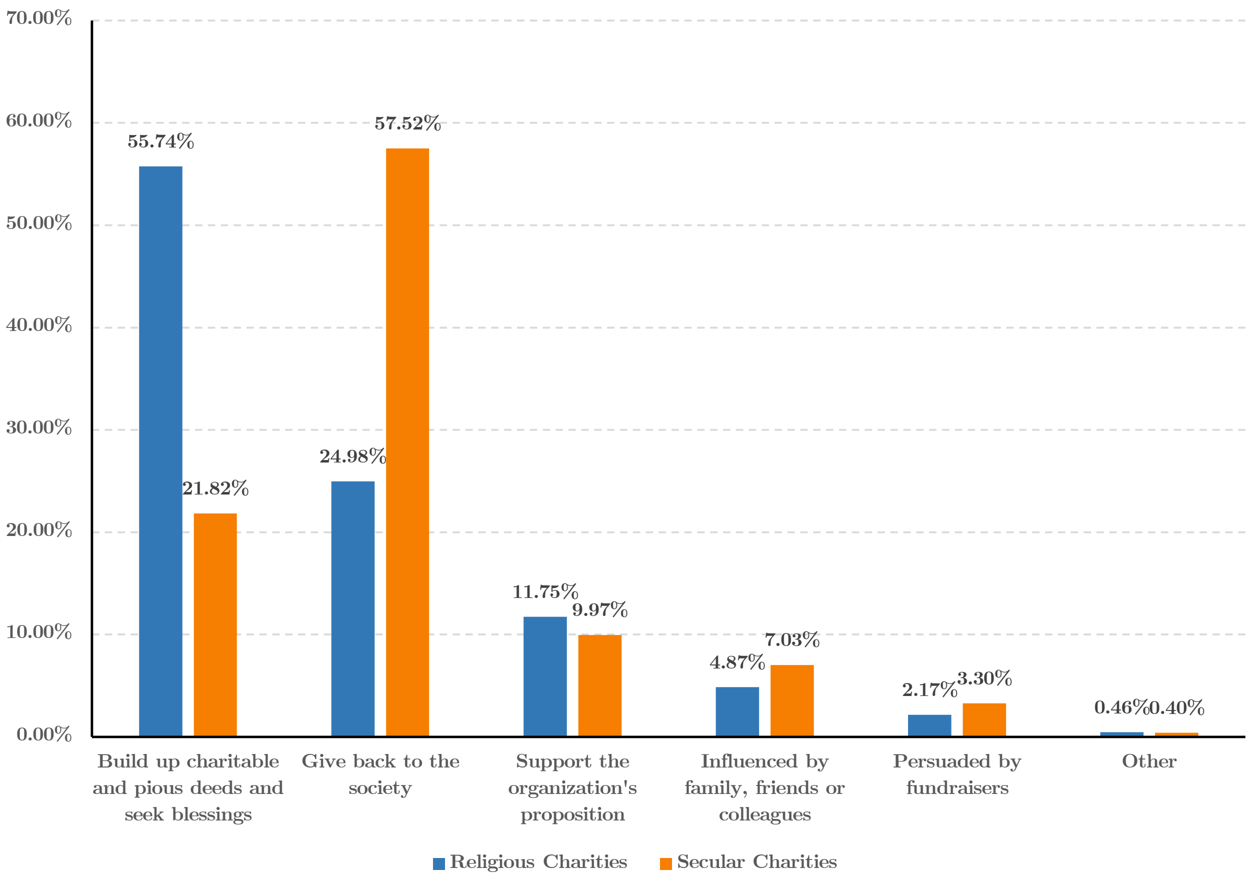
5. Conclusions

Using data on income uncertainty, credit card donations, and insurance purchases from a large commercial bank in Taiwan, we examine how individuals may respond to increased income uncertainty by donating. Our analysis suggests that donations may function as a psychological mechanism for coping with uncertainty, particularly donations to foundations connected with a religion or spiritual tradition, which appear to show a stronger response to increased income uncertainty compared to secular donations. We also find that making religious donations in the transaction data is associated with reduced insurance purchases. This reduction operates through two channels: experienced buyers not renewing or shrinking coverage at the annual-renewal decision, and individuals without prior insurance being deterred from first-time entry. Furthermore, we observe in a field experiment on an online donation platform in mainland China that spiritual insurance narratives have an effect. However, the effect of spiritual insurance appears to be primarily psychological rather than material, as we observe that donations do not significantly reduce future income or consumption uncertainty.

These results offer a new perspective on how people "deal with risk" broadly defined, especially amid economic uncertainty. They may help explain the counterintuitive patterns observed by List (2011), where donations increased during periods of heightened economic volatility. Additionally, they may be relevant for the financial market for insurance products affected by frictions such as conflicts of interest (e.g. Egan, Ge, and Tang, 2022) and uninsurable risks (e.g. Aiyagari, 1994).

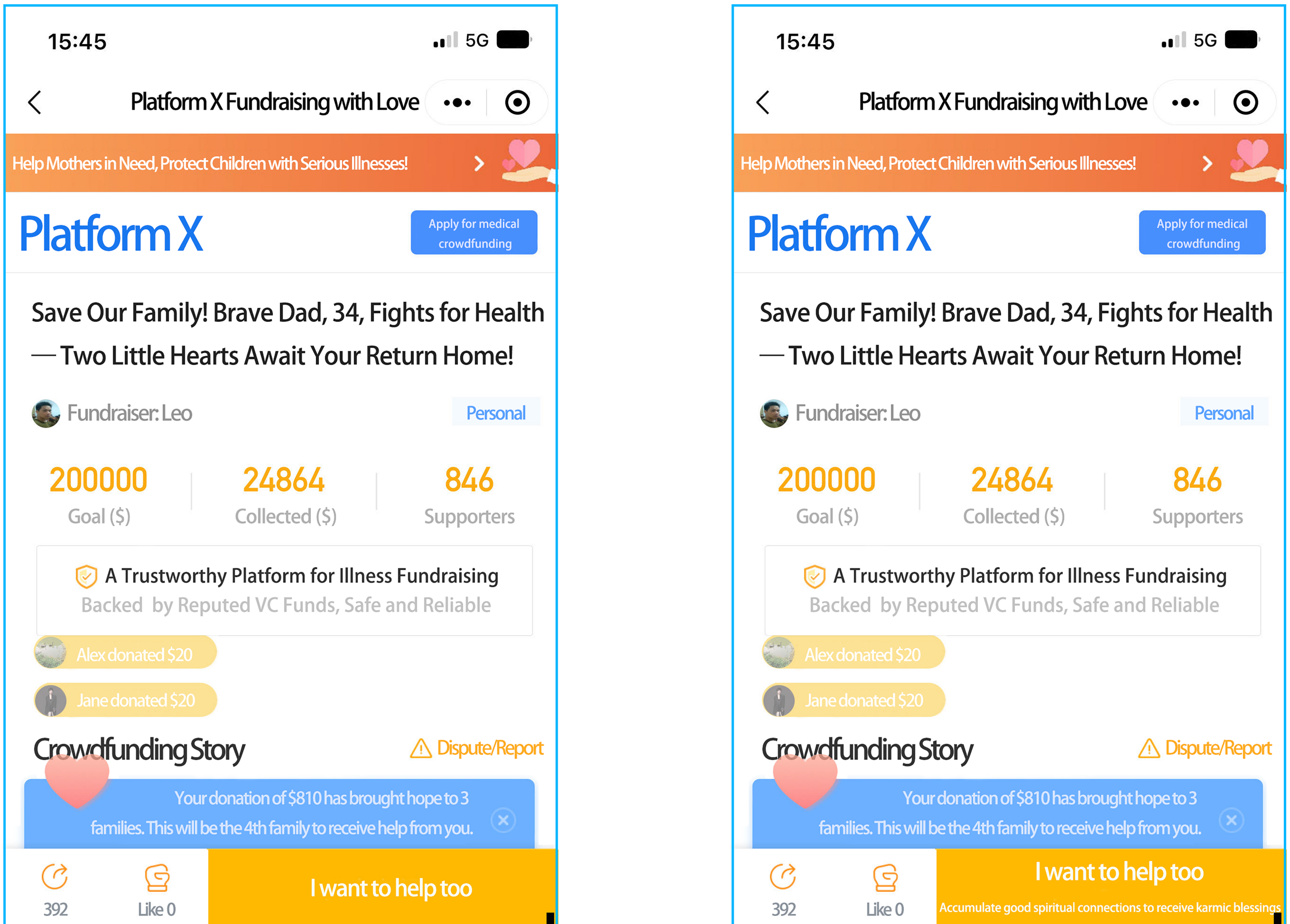
Another research direction worth exploring is the broader impact of spiritual insurance on investment risk tolerance. If belief in spiritual insurance affects subjective risk assessments, it may encourage riskier investments or greater entrepreneurial activity. Future work could examine these possible "prosperity gospel" effects, which are common in some evangelical communities anecdotally. Such inquiry could deepen our understanding of how spiritual beliefs influence economic decisions and open new avenues for analyzing risk-taking beyond factors typically considered.

Figure 1: Survey-stated Reasons for Donating to Religious versus Secular Organizations

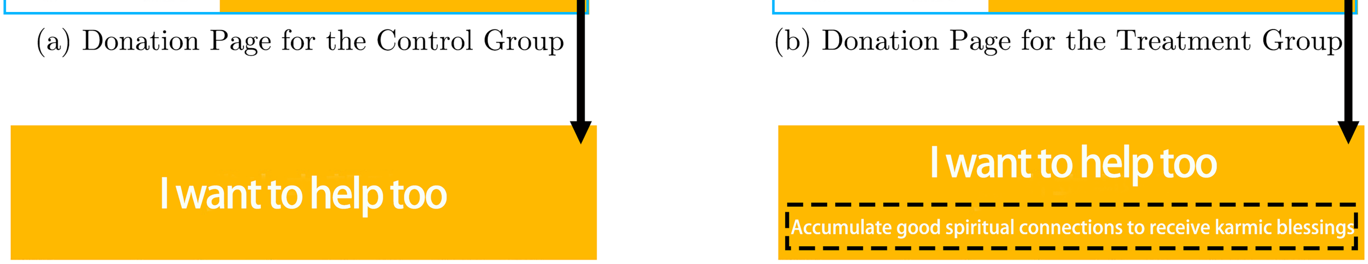


Source: Census of the sample economy. This distribution of primary reasons is calculated out of a sample of a total of 2,630 donors who gave to religious organizations and a total of 2,488 donors who gave to secular organizations.

Figure 2: Illustration of the Field Experiment on Spiritual Insurance Narratives



(a) Donation Page for the Control Group (b) Donation Page for the Treatment Group

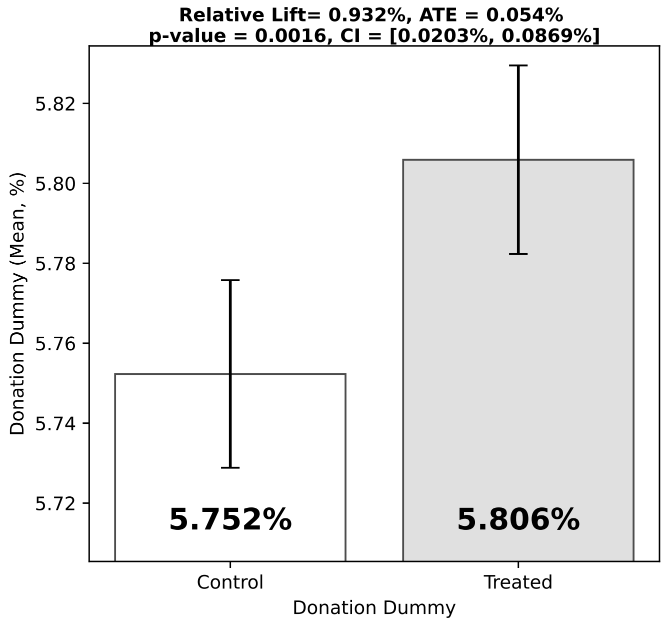


(c) Donation Button for the Control Group (d) Donation Button for the Treatment Group (with Spiritual Insurance Stimuli Highlighted)

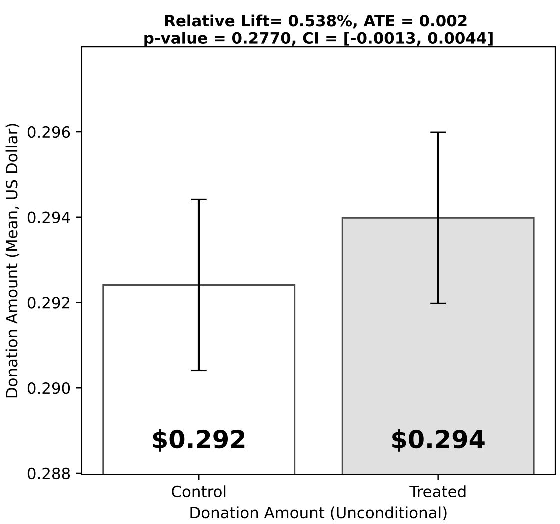
Notes: This figure illustrates Platform X's interface (translated to English), and the experiment treatment. Patients in need can initiate campaigns on Platform X by submitting verifiable medical and financial details. These campaigns, upon verification, become accessible to and spread via social network among Platform X's potential donor base. The potential donors view the donation page on their cell phone screens for the campaign details. For the treatment group of potential donors, the donation button was altered by adding a phrase "accumulate good spiritual connections to receive karmic blessings", which increases the salience of the spiritual insurance narrative. The control group experienced the standard donation page without this message. The experiment ran from July 28 to August 15, 2022.

Figure 3: The Field Experiment: Average Treatment Effect

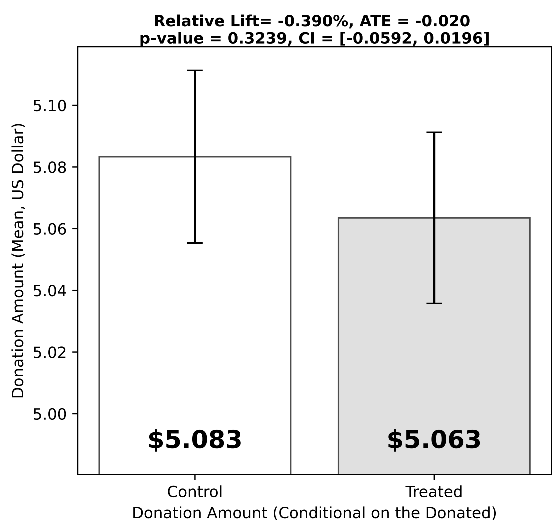
(a) Effect on Donation Likelihood



(b) Effect on Donation Amount (Unconditional)



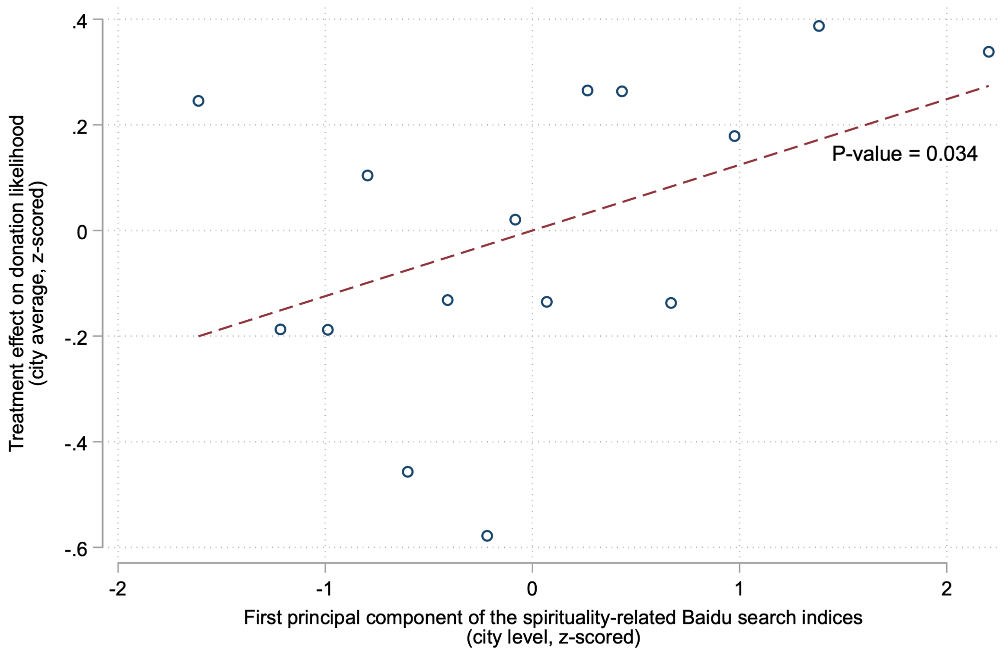
(c) Effect on Donation Amount (Conditional)



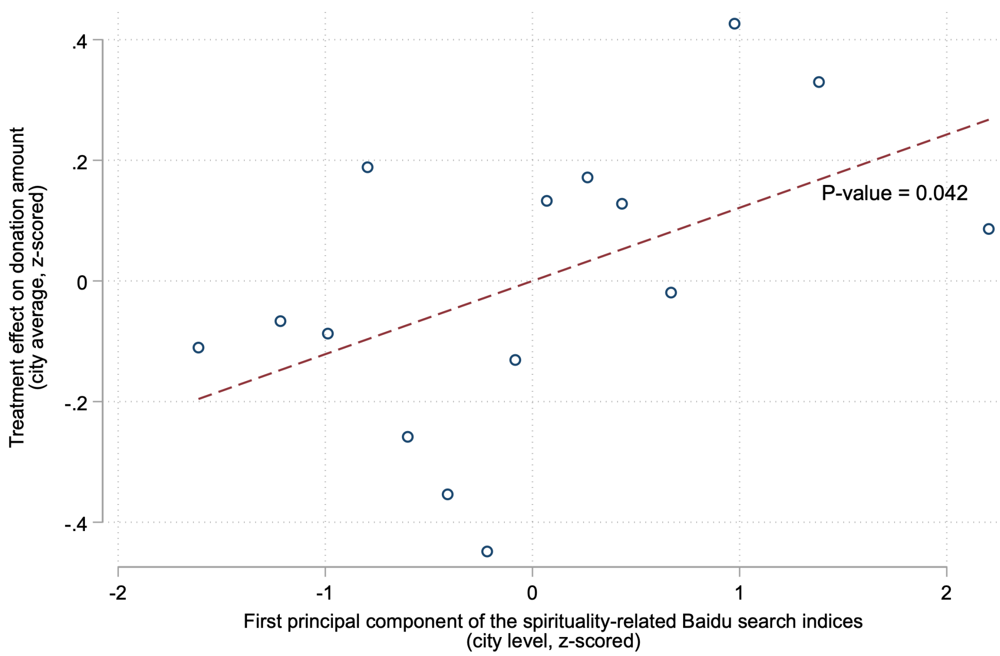
Notes: This figure illustrates the estimated average treatment effects in the field experiment on Platform X. Comparisons between the treated and control are described on the top of each panel, with relative change ratios, average treatment effects, and p-values and 95% confidence intervals for the average treatment effects. The error bars are 95% confidence intervals around the sample group averages. For the treatment group of potential donors, a phrase ("accumulate good spiritual connections to receive karmic blessings") was added below the donation button in the campaign page on this online donation platform, while the page stays unchanged for the control group. Panel (a), (b), and (c) show the average treatment effects on donation likelihood, unconditional donation amount, and conditional donation amount, respectively. The results are consistent with donor base expansion and a "walking down the demand curve" effect, whereby spiritual cues induce marginal donors with lower giving capacity or weaker altruistic motivation to enter the market.

Figure 4: The Field Experiment: The Relationship between Heterogeneous Treatment Effects and Regional Variations in Spirituality-related Search Activities

Panel A: Treatment Effect on Donation Likelihood



Panel B: Treatment Effect on Donation Amount



Notes: The figure illustrates how the treatment effects in the field experiment are positively related at the city-level with web search activity of keywords that traditionally signify a belief in fate being influenced by supernatural forces and are associated with spiritual narratives. **Panel A** plots the treatment effect on donation likelihood, while **Panel B** plots the treatment effect on donation amount. In both panels, the dependent variable and the independent variable are z-scored. The dots are produced through a binscatter procedure. The linear fit lines correspond to the regression results in Table 9.

Table 1: Summary Statistics

Number of individuals							74,023
Number of quarters							8
Number of observations							592,184
Non-zero fraction of donation							1.46%
Non-zero fraction of religious donation							0.89%
Non-zero fraction of secular donation							0.61%
Non-zero fraction of insurance							13.44%
Non-zero fraction of health expenditure							6.54%
	Mean	Std. dev.	Min	25th pct.	Median	75th pct.	Max
Income	\$4,067	\$30,867	\$635	\$1,478	\$2,200	\$3,867	\$11,349,309
Financial wealth	\$13,600	\$35,667	\$0	\$894	\$3,500	\$12,667	\$3,540,548
Total donation (non-zero)	\$97.10	\$95.85	\$0.03	\$50.00	\$80.00	\$100.00	\$3,033.33
Religious donation (non-zero)	\$94.39	\$102.60	\$3.33	\$50.00	\$70.00	\$100.00	\$3,033.33
Secular donation (non-zero)	\$94.40	\$72.54	\$0.03	\$50.00	\$83.33	\$100.00	\$1,200.00
Insurance (non-zero)	\$1,569.40	\$2,600.97	\$1.97	\$266.67	\$416.67	\$636.06	\$24,939.17
Health expenditure (non-zero)	\$72.56	\$207.33	\$0.07	\$18.00	\$33.33	\$66.67	\$18,400.00
Age	36.53	6.99	18	31	36	41	55
$\hat{\sigma}$	0.42	0.17	0.03	0.30	0.41	0.54	1.78
$\hat{\sigma}^{\text{pos}}$	0.32	0.13	0.02	0.22	0.30	0.40	1.19
$\hat{\sigma}^{\text{neg}}$	0.25	0.11	0.02	0.17	0.24	0.32	1.26
Gender	Female						
	0.46						
Marriage status	Married						
	0.32						
Education	Masters and above		Undergraduate		Vocational school		
	0.14		0.38		0.20		
	High school and below						
	0.29						
Job position	Public sector officers		Agricultural workers		Blue-collar workers		
	0.02		0.00		0.31		
	White-collar workers		Service-sector workers		Executives		
	0.52		0.04		0.08		
	Owner-managers		Others				
	0.01		0.02				
Dependents	No dependent		One dependent		Two dependents		
	0.87		0.05		0.07		
	Three or more						
	0.01						

Notes: This table presents the summary statistics for the sample at the individual-quarter level. Income is the average monthly payroll receipt during the quarter. Financial wealth is measured as the sum of the value of saving, bond, fund, and stocks net of debt. Donations include donations to secular and religious charities. Insurance is spending on life insurance and private health insurance. Health expenditure is defined as spending on medical care. The means, standard deviations, and quantiles of donation, health expenditure, and insurance are conditional on the corresponding variable being non-zero. $\hat{\sigma}$ is the income uncertainty measure, computed as the standard deviation of all monthly income realizations over the preceding four quarters, after removing predictable income components. $\hat{\sigma}^{\text{neg}}$ ($\hat{\sigma}^{\text{pos}}$) retains only the negative (positive) component of the unpredicted income realizations when computing the income uncertainty measure. All currency units are converted to USD at the exchange rate.

Table 2: Income Uncertainty Predicts Donation

Panel A: Probability of donation $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Pr(donation$_{t+1}$)			
Specification	OLS	OLS	OLS	IV	IV	IV
Income uncertainty$_t$	0.70%***	0.70%***	0.70%***	1.86%***	1.92%***	1.90%***
	(0.06%)	(0.06%)	(0.06%)	(0.56%)	(0.59%)	(0.60%)
Income$_t$		-0.02%	0.02%		0.07%	0.07%
		(0.03%)	(0.03%)		(0.05%)	(0.06%)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	403.0	394.0	378.8
R^2-Adjusted	0.384	0.384	0.384	/	/	/
Mean Pr(Donation$_{t+1}$)	1.46%	1.46%	1.46%	1.46%	1.46%	1.46%
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
City × quarter FE	NO	NO	YES	NO	NO	YES
Panel B: Donation amount $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Donation amount$_{t+1}$			
Specification	OLS	OLS	OLS	IV	IV	IV
Income uncertainty$_t$	0.53***	0.52***	0.52***	2.09***	2.17***	2.13***
	(0.06)	(0.06)	(0.06)	(0.77)	(0.81)	(0.83)
Income$_t$		0.01	0.02		0.12*	0.12
		(0.06)	(0.06)		(0.07)	(0.07)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	403.0	394.0	378.8
R^2-Adjusted	0.402	0.402	0.402	/	/	/
Uncond. Mean(Dona. Amt$_{t+1}$)	$1.42	$1.42	$1.42	$1.42	$1.42	$1.42
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
City × quarter FE	NO	NO	YES	NO	NO	YES

Notes: This table reports estimates of regressions where within-person variations in income uncertainty predict the likelihood and amount of donations. The dependent variable is the next-quarter likelihood to donate in Panel A and the next-quarter donation amount in Panel B. The main independent variable of interest, income uncertainty, is the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters. Columns (1)-(3) report OLS estimates. Columns (4)-(6) report instrumental variable estimates, where individual-level income uncertainty is instrumented by the firm-level leave-one-out average of income uncertainty. Control variables are log income, log financial wealth, and demographic variables that include age, age squared, education, occupation, marital status, and number of dependents. Standardized coefficients are reported for all continuous independent variables, including income uncertainty. Full set of coefficients are reported in Online Appendix Table A.2. All currency units are converted to USD. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 3: Income Uncertainty Predicts Donation: Religious Donation and Negative Uncertainty

Panel A: Probability of donation ($t+1$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable				Pr(donation$_{t+1}$)				
Foundation type	Religious	Secular	Religious	Secular	Religious	Secular	Religious	Secular
Specification	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Income	0.47%***	0.24%***			1.23%***	0.64%		
uncertainty$_t$	(0.04%)	(0.04%)			(0.45%)	(0.40%)		
Positive			0.19%***	0.09%***			0.36%	0.17%
uncertainty$_t$			(0.03%)	(0.02%)			(0.23%)	(0.20%)
Negative			0.27%***	0.15%***			1.06%*	0.39%
uncertainty$_t$			(0.05%)	(0.04%)			(0.55%)	(0.47%)
Observations	296,092	296,092	296,092	296,092	273,616	273,616	273,616	273,616
First-stage F-stat.	/	/	/	/	378.8	378.8	159.7	159.7
R^2-Adjusted	0.382	0.383	0.382	0.383	/	/	/	/
Mean Pr(Donation$_{t+1}$)	0.89%	0.61%	0.89%	0.61%	0.89%	0.61%	0.89%	0.61%
Cond. Mean(Dona. Amt$_{t+1}$)	$94.39	$94.40	$94.39	$94.40	$94.39	$94.40	$94.39	$94.40
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Donation amount ($t+1$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable				Donation amount$_{t+1}$				
Foundation type	Religious	Secular	Religious	Secular	Religious	Secular	Religious	Secular
Specification	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Income	0.32***	0.21***			1.40**	0.73*		
uncertainty$_t$	(0.04)	(0.04)			(0.71)	(0.43)		
Positive			0.13***	0.07***			0.36	0.23
uncertainty$_t$			(0.02)	(0.03)			(0.33)	(0.21)
Negative			0.19***	0.14***			1.27*	0.35
uncertainty$_t$			(0.05)	(0.04)			(0.77)	(0.50)
Observations	296,092	296,092	296,092	296,092	273,616	273,616	273,616	273,616
First-stage F-stat.	/	/	/	/	378.8	378.8	159.7	159.7
R^2-Adjusted	0.368	0.444	0.368	0.444	/	/	/	/
Uncond. Mean(Dona. Amt$_{t+1}$)	$0.84	$0.58	$0.84	$0.58	$0.84	$0.58	$0.84	$0.58
Cond. Mean(Dona. Amt$_{t+1}$)	$94.39	$94.40	$94.39	$94.40	$94.39	$94.40	$94.39	$94.40
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports estimates of regressions where within-person variations in income uncertainty predict the likelihood and amount of donations to religious foundations and donations to secular foundations. The dependent variable is the next-quarter likelihood to donate in Panel A and the next-quarter donation amount in Panel B for the respective foundation type. The main independent variables of interest include income uncertainty, as the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters, and positive income uncertainty and negative income uncertainty, as constructed using the semi-variance approach. Columns (1)-(4) report OLS estimates. Columns (5)-(8) report instrumental variable estimates, where individual-level (positive, negative) income uncertainty is instrumented by the firm-level leave-one-out average of (positive, negative) income uncertainty. Control variables are log income, log financial wealth, and demographic variables that include age, age squared, education, occupation, marital status, and number of dependents. Standardized coefficients are reported for all continuous independent variables, including income uncertainty. Full set of coefficients are reported in Online Appendix Table A.4. All currency units are converted to USD. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 4: Health Shocks Predict Donation: Religious Donation and Secular Donation

Panel A: Probability of donation $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Pr(donation$_{t+1}$)			
Foundation type	All	Religious	Secular	All	Religious	Secular
Health shock occurrence$_t$	3.94%***	3.15%***	0.85%***			
	(0.25%)	(0.21%)	(0.14%)			
Health shock amount$_t$				0.76%***	0.61%***	0.16%***
				(0.21%)	(0.17%)	(0.05%)
Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.387	0.386	0.383	0.385	0.384	0.383
Mean Pr(Donation$_{t+1}$)	1.46%	0.89%	0.61%	1.46%	0.89%	0.61%
Cond. Mean(Dona. Amt$_{t+1}$)	\$97.10	\$94.39	\$94.40	\$97.10	\$94.39	\$94.40
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES
Panel B: Donation amount $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Donation amount$_{t+1}$			
Foundation type	All	Religious	Secular	All	Religious	Secular
Health shock occurrence$_t$	2.08***	1.98***	0.11			
	(0.23)	(0.20)	(0.12)			
Health shock amount$_t$				0.44***	0.42***	0.02
				(0.13)	(0.12)	(0.02)
Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.402	0.369	0.443	0.402	0.369	0.443
Uncond. Mean(Dona. Amt$_{t+1}$)	\$1.42	\$0.84	\$0.58	\$1.42	\$0.84	\$0.58
Cond. Mean(Dona. Amt$_{t+1}$)	\$97.10	\$94.39	\$94.40	\$97.10	\$94.39	\$94.40
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES

Notes: This table reports the estimates of regressions where within-person variations in health shocks predict the likelihood and amount of donations to all foundations, to religious foundations, and to secular foundations. The dependent variable is the quarter $t+1$ likelihood to donate in Panel A and the donation amount in Panel B for the respective foundation type. The main independent variable of interest, health shock occurrence, is defined as the dummy of incurring medical expenditures in quarter t that are above the median of the sample in Columns (1)-(3), and as the amount spent on medical expenditures in quarter t that are above the median of the sample in Columns (4)-(6). Control variables and fixed effects are the same as in Table 2. Standardized coefficients are reported for all continuous independent variables. The full set of coefficients are reported in Online Appendix Table A.7. All currency units are converted to USD. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 5: Donation Associated with Reduction in Insurance Expenditures

Panel A: Whether donated in the same quarter ($t+1$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Insurance expenditures$_{t+1}$ ($)			
Foundation type	All	Religious	Secular	All	Religious	Secular
Donation dummy$_{t+1}$	-71.03***	-89.95***	-44.82	15.54	18.16	13.52
	(23.00)	(28.84)	(34.84)	(35.39)	(46.16)	(52.60)
Income uncertainty$_t$ ×				-96.68***	-119.33**	-64.78
Donation dummy$_{t+1}$				(36.29)	(50.04)	(47.91)
Income uncertainty$_t$	100.04***	99.97***	99.65***	101.53***	101.10***	100.05***
	(5.83)	(5.83)	(5.83)	(5.87)	(5.86)	(5.83)
Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.169	0.169	0.169	0.169	0.169	0.169
Mean(Insur. exp.$_{t+1}$)	$216.42	$216.42	$216.42	$216.42	$216.42	$216.42
Control variables	YES	YES	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	YES	YES	YES	YES	YES	YES
Panel B: Donation amount in the same quarter ($t+1$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Insurance expenditures$_{t+1}$ ($)			
Foundation type	All	Religious	Secular	All	Religious	Secular
Donation amount$_{t+1}$	-3.73*	-5.25**	-1.51	1.22	0.55	2.50
	(2.05)	(2.63)	(3.71)	(2.76)	(3.37)	(5.18)
Income uncertainty$_t$ ×				-5.30**	-6.38**	-4.13
Donation amount$_{t+1}$				(2.18)	(2.80)	(3.82)
Income uncertainty$_t$	99.74***	99.71***	99.57***	100.49***	100.24***	99.82***
	(5.83)	(5.83)	(5.83)	(5.84)	(5.84)	(5.83)
Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.169	0.169	0.169	0.169	0.169	0.169
Mean(Insur. exp.$_{t+1}$)	$216.42	$216.42	$216.42	$216.42	$216.42	$216.42
Control variables	YES	YES	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	YES	YES	YES	YES	YES	YES

Notes: This table reports estimates of regressions examining the association between donations and insurance expenditures using within-person variations in insurance spending, donations, and income uncertainty. The dependent variable is the insurance expenditures in quarter $t+1$. In columns (1)-(3) of Panel A, the main independent variables of interest are a donation dummy for donating to the corresponding type of foundations in quarter $t+1$, and income uncertainty, as the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters up to quarter t. In columns (4)-(6) of Panel A, the interaction of income uncertainty$_t$ and donation dummy$_{t+1}$ is further added. In Panel B, donation dummy$_{t+1}$ is replaced with donation amount$_{t+1}$, the raw amount donated to the corresponding type of foundations in quarter $t+1$ (not standardized). Control variables and fixed effects are the same as in Table 2. Continuous control variables, including income uncertainty, are standardized. Full set of coefficients are reported in Online Appendix Table A.8. All currency units are converted to USD. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 6: Monthly Forward Analysis: Donation$_t$ $\rightarrow$ Insurance$_{t+m}$

	All		Religious		Secular	
Horizon	m=1	m=2	m=1	m=2	m=1	m=2
Panel A: Total insurance spending ($); mean $74.27						
Donation dummy	−13.94**	−2.40	−17.26**	−6.80	0.64	4.00
	(6.72)	(6.24)	(7.05)	(8.26)	(12.56)	(9.55)
Observations	740,230	740,230	740,230	740,230	740,230	740,230
Panel B: Extensive margin (any purchase); mean 0.107						
Donation dummy	−0.0165**	−0.0050	−0.0201**	−0.0090	0.0043	−0.0020
	(0.0073)	(0.0068)	(0.0097)	(0.0089)	(0.0109)	(0.0101)
Observations	740,230	740,230	740,230	740,230	740,230	740,230
Panel C: Intensive margin ($ | purchase); mean $694.11						
Donation dummy	−40.74	−9.83	−50.28	−14.67	5.13	−4.62
	(49.03)	(48.87)	(60.15)	(59.82)	(64.87)	(65.23)
Observations	79,204	79,204	79,204	79,204	79,204	79,204

Notes: This table reports OLS estimates of regressions examining the monthly predictive relationship between donation in month t and insurance expenditures in month $t+m$. The regressions control for individual fixed effects, city×month fixed effects, income-uncertainty control $\hat{\sigma}_{i,t}$, and baseline demographic and financial controls (same controls as Table 5). Standard errors clustered by individual in parentheses. *, **, *** denote 10%, 5%, 1% significance.

Table 7: Donation–Insurance Substitution: Prior Status, Renewal Window, and Margin

	Total			Extensive			Intensive		
	All	Rel.	Sec.	All	Rel.	Sec.	All	Rel.	Sec.
Panel A: Prior purchasers (N = 71,669; intensive N = 27,736; mean Total=\$728.8, Ext=0.387, Int=\$1,883.1)									
Donation	−107.9***	−138.5***	−48.7	−0.011	−0.015	−0.003	−237.6**	−298.4**	−92.3
	(38.5)	(48.9)	(59.9)	(0.009)	(0.011)	(0.012)	(117.3)	(142.6)	(172.5)
Panel B: Prior$_{k4}$ (N = 26,416; intensive N = 14,108; mean Total=\$1,037.3, Ext=0.534, Int=\$1,942.4)									
Donation	−215.4***	−262.2***	−62.2	−0.026*	−0.038**	0.006	−310.5**	−385.2**	−78.4
	(66.8)	(84.3)	(92.6)	(0.015)	(0.019)	(0.023)	(158.7)	(195.4)	(238.2)
Panel C: Prior$_{non\text{-}k4}$ (N = 45,253; intensive N = 13,628; mean Total=\$548.7, Ext=0.301, Int=\$1,822.9)									
Donation	−45.2	−66.4	−40.9	−0.003	−0.002	−0.009	−162.4	−208.3	−106.7
	(45.9)	(57.9)	(72.1)	(0.010)	(0.013)	(0.015)	(175.6)	(215.7)	(264.5)
Panel D: No Prior (N = 224,423; intensive regression not estimable; mean Total=\$52.8, Ext=0.054, Int≈\$977.9)									
Donation	−11.3	−22.2	8.6	−0.006***	−0.008***	−0.002	—	—	—
	(29.4)	(33.3)	(50.9)	(0.002)	(0.003)	(0.004)			

Notes: This table reports results estimating the donation-insurance substitution patterns by extensive and intensive margins and by prior insurance purchase status. Each panel is a subsample defined by prior-purchase timing. Panel A: all individuals with any prior insurance transaction. Panel B: prior purchasers whose most recent insurance transaction was exactly four quarters before the donation quarter (proxy for annual-renewal window). Panel C: prior purchasers off the renewal window. Panel D: individuals without any prior insurance transaction (the intensive margin regression is not estimable for this subsample given that we control for individual fixed effects—each individual belonging to this No Prior subsample has at most one observation with non-zero insurance expenditure before exiting this subsample in the next quarter). Within each panel, the nine columns cross donation type (All, Religious, Secular) with margin (Total, Extensive, Intensive). All specifications include individual fixed effects, city×quarter fixed effects, income uncertainty, and baseline demographic and financial controls (same controls as Table 5). Standard errors clustered at the individual level in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level.

Table 8: "Self-fulfilling Hypothesis"? Donation Does Not Robustly Predict Reduction in Uncertainty

Panel A: Whether donated in the first half of the sample ($year = 1$)			
	(1)	(2)	(3)
Dependent variable	Income uncertainty$_{year=2}$		
Foundation type	All	Religious	Secular
Donation dummy$_{year=1}$	0.05	0.05	0.07
	(0.03)	(0.03)	(0.05)
Donation dummy $\times$ Income uncertainty$_{year=1}$	-0.02	-0.01	-0.05
	(0.02)	(0.03)	(0.03)
Income uncertainty$_{year=1}$	0.389***	0.388***	0.389***
	(0.004)	(0.004)	(0.004)
Observations	74,023	74,023	74,023
R^2-Adjusted	0.351	0.351	0.351
Control variables	YES	YES	YES
Panel B: Donation amount in the first half of the sample ($year = 1$)			
	(1)	(2)	(3)
Dependent variable	Income uncertainty$_{year=2}$		
Foundation type	All	Religious	Secular
Donation amount$_{year=1}$	-0.00000	-0.00002	0.00003
	(0.00005)	(0.00005)	(0.00010)
Donation amount $\times$ Income uncertainty$_{year=1}$	0.00002	0.00007	-0.00005
	(0.00005)	(0.00007)	(0.00008)
Income uncertainty$_{year=1}$	0.388***	0.388***	0.389***
	(0.004)	(0.004)	(0.004)
Observations	74,023	74,023	74,023
R^2-Adjusted	0.351	0.351	0.351
Control variables	YES	YES	YES

Notes: This table reports estimates of regressions examining the association between donation and future income uncertainty. The dependent variable is individual income uncertainty in the second half of the sample ($year = 2$), measured as the standard deviation of the unpredicted component of all realized log monthly payroll income in the second year of the two-year sample. In panel A, the independent variables of interest are a donation dummy for donating to the corresponding type of foundations in $year = 1$, the first year of the two-year sample, and income uncertainty in $year = 1$. In panel B, donation dummy$_{year=1}$ is replaced with donation amount$_{year=1}$, the amount donated to the corresponding type of foundations in $year = 1$. Control variables include log income in $year = 1$, log financial wealth in $year = 1$, and demographic variables that include age, age squared, educational attainment, occupational type, marital status, and the number of dependents. All continuous variables (except the donation amount) are standardized, including income uncertainty. Full set of coefficients are reported in Online Appendix Table A.15. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 9: Heterogeneous Treatment Effects in the Field Experiment Associated with Regional Variations in Spirituality-related Search Activities

	(1)	(2)	(3)	(4)	(5)	(6)
	Per-capita donations (city-level)		Treatment effect (prob., city avg.)		Treatment effect (uncon. amt, city avg.)	
First principal component of the	0.440***	0.325***	0.124**	0.174**	0.121**	0.121*
spirituality-related Baidu search indices	(0.075)	(0.108)	(0.058)	(0.068)	(0.059)	(0.069)
Per capita gross regional product		-0.204		-0.094		0.090
		(0.139)		(0.128)		(0.106)
Per capita retail sales		0.330**		0.033		-0.004
		(0.134)		(0.108)		(0.096)
Per capita public expenditure		0.030		-0.070		-0.063
		(0.147)		(0.154)		(0.162)
Per capita public expenditure		-0.159		0.112		0.043
(science and technology)		(0.106)		(0.095)		(0.097)
Per capita public expenditure		0.265**		0.044		0.047
(education)		(0.123)		(0.170)		(0.185)
Coverage of urban employee basic		-0.089		0.029		0.140
pension		(0.093)		(0.112)		(0.125)
Coverage of urban employee public		-0.116		-0.074		-0.125
health insurance		(0.113)		(0.152)		(0.172)
Coverage of urban employee		0.393**		-0.037		-0.109
unemployment insurance		(0.161)		(0.138)		(0.167)
Constant	0.015	0.015	-0.000	-0.000	-0.000	-0.000
	(0.054)	(0.049)	(0.058)	(0.059)	(0.058)	(0.059)
Observations	290	290	290	290	290	290
R-squared	0.188	0.353	0.015	0.027	0.015	0.028

Notes: This table reports the relationship between heterogeneous treatment effects in the field experiment and regional variations in spirituality-related search activities. For the treatment group of potential donors, a phrase ("accumulate good spiritual connections to receive karmic blessings") was added below the donation button in the campaign page on this online donation platform, while the page stays unchanged for the control group. The prefectural-city level average treatment effects *on donation probability and donation amount* and the independent variables in all columns are standardized. The prefectural-city level total donations on Platform X is normalized by population and also standardized. Heteroskedasticity-consistent standard errors are reported beneath the estimated coefficient within parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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Hedging by Giving: Spiritual Insurance and Religious Donations

Internet Appendix

A. Internet Appendix Sections

In the Internet Appendix, we describe the philanthropic foundations in our bank dataset in more detail in Section A.1. We provide proofs of the Lemmas and Propositions in the paper from Section A.2 to Section A.5. We present results from additional robustness checks in Section A.6.

A.1 List of Foundations Receiving Credit Card Donations in Our Dataset

We provide more details on the names, missions, beneficiaries, and payment methods of the sample foundations in this section. We categorize "religious" (broadly-defined) and secular foundations by whether the mission statement states religious goals ("promote the gospel" —Eden Foundation) or the charity has names ("Buddhist Tzu Chi Charity Foundation") directly related to a religion or a spiritual tradition. If it does any of the two, we categorize the foundation as "religious"; if it does neither, we categorize the foundation as secular.

A significant majority (92.8%) of the sample's "religious" donations were directed to two major non-church evangelical foundations, while three Buddhist foundations accounted for the remainder (7.2%) of religious donations. Our dataset does not include donations to smaller foundations that are more likely local and primarily in cash.

Buddhist foundations were slower to adopt online and credit card donation systems, resulting in their smaller share in our dataset. Secular donations in our sample were distributed across four foundations that neither include religion in their names nor reference religious goals in their missions.

Religious Foundations

World Vision[1]

(40.5% of the sample donations; 70.2% of the sample religious donations)

World Vision is an international partnership of Christians whose mission is ”to follow our Lord and Saviour Jesus Christ in working with the poor and oppressed to promote human transformation, seek justice, and bear witness to the good news of the Kingdom of God.” Founded in 1950, World Vision works in nearly 100 countries and regions across the globe. World Vision Taiwan was established in 1964 and provides protection and development aid for children in poverty both in Taiwan and abroad. The organization primarily accepts donations online via credit cards. It also accepts bank transfers at post offices and bank counters, as well as cash at its public relations offices. World Vision is generally considered the largest evangelical humanitarian agency in the world (Strand, 2014; King, 2019).

Eden Social Welfare Foundation[2]

(13.0% of the sample donations; 22.6% of the sample religious donations)

Eden Social Welfare Foundation is a Christian organization committed to serving persons with disabilities and other socially marginalized groups in Taiwan and throughout East Asia. Founded in 1982 by Ms. Hsia Liu, a writer and wheelchair user suffering from rheumatic arthritis, Eden operates with the mission of “serving the disadvantaged, bearing witness to Christ, promoting both the gospel and welfare, and leading people back to the Lord.” As Ms. Hsia Liu stated, “Evangelism is our fundamental mission, and social services are the method to put God’s love into practice.” Eden primarily accepts

[1] https://www.wvi.org.

[2] https://eden.international.

donations online via credit cards. It also welcomes donations via bank transfers at post offices, ATMs, and bank counters, as well as cash donations at select convenience stores and check donations via mail.

Buddhist Tzu Chi Charity Foundation[3]

(2.4% of the sample donations; 4.1% of the sample religious donations)

The Tzu Chi Foundation is the world's leading Buddhist humanitarian organization founded in 1966 by Buddhist nun Master Cheng Yen in Hualien, Taiwan. At its headquarters, nuns study Buddhism and perform duties of the foundation. Tzu Chi is most well-known for its disaster relief efforts worldwide, reaching 136 countries and regions. Donors can contribute to Tzu Chi to support elderly care, assistance for children in poverty, and disaster and conflict relief worldwide. Tzu Chi accepts credit card donations online or via phone. It also accepts donations via bank transfers at post offices or bank counters, and cash donations at Tzu Chi Liaison Offices.

Dharma Drum Mountain Temple and Buddhist Foundation[4]

(1.7% of the sample donations; 2.9% of the sample religious donations)

Dharma Drum Mountain Temple, founded by Master Sheng Yen in 1989 and located in New Taipei City in northern Taiwan, is one of the largest Buddhist temples on the island. In addition to welcoming visitors, the temple also houses a Buddhist education campus for monks. The Dharma Drum Mountain Buddhist Foundation is the philanthropic arm of the temple and provides disaster relief, tuition and scholarship support for economically disadvantaged students, nursing home visits, and free training for social workers. Both the temple and the foundation accept cash donations offline, bank transfers at post offices and bank counters, and credit card donations online.

Fo Guang Shan Temple and Fo Guang Shan Compassion Foundation[5]

(0.1% of the sample donations; 0.2% of the sample religious donations)

Fo Guang Shan Temple, located in Kaohsiung City in southern Taiwan, is the largest

[3] https://www.tzuchi.org.tw.
[4] https://charity.ddm.org.tw.
[5] http://www.compassion.org.tw.

Buddhist temple on the island. Founded by Master Hsing Yun in 1967, it is visited by nearly ten million people each year. The Fo Guang Shan Compassion Foundation is the charitable arm of the temple, providing social programs including disaster relief, mobile clinics for remote villages, nursing home visits, prison education programs, tuition aid for economically disadvantaged children, and assistance for the physically disabled. Both the temple and the foundation primarily accept cash donations offline. Additionally, the foundation accepts credit card donations via mailed forms, and the temple accepts credit card donations online.

Secular Foundations

Taiwan Fund for Children and Families[6]

(39.0% of the sample donations, 92.2% of the sample secular donations)

Taiwan Fund for Children and Families (TFCF) is an international non-governmental organization headquartered in Taichung, Taiwan. TFCF's mission is to support vulnerable children and their families both in Taiwan and worldwide. The foundation collaborates with the government to advocate for and implement various welfare services and programs, including foreign children sponsorship, livelihood assistance, medical care, health promotion for families with children living below the poverty line, disaster relief, and tuition support. TFCF's ultimate vision is for every child to receive proper care, be protected from harm, grow up in a healthy environment, and have access to quality education, enabling them to lead happy and fulfilling lives. TFCF accepts credit card donations online, bank transfers at post offices and bank counters, and cash donations at the headquarters.

Sunshine Social Welfare Foundation[7]

(1.4% of the sample donations, 3.4% of the sample secular donations)

Sunshine Social Welfare Foundation was established in 1981 by a group of dedicated individuals and organizations who aimed to change the lives of people with facial dis-

[6] https://www.ccf.org.tw.
[7] https://www.sunshine.org.tw.

figurement, as well as raise social awareness about the issue. They were moved to do so following the publication of the book People Who Shun the Sunshine, written by SHEN Hsiao-Ya, a burn survivor. The mission of Sunshine Social Welfare Foundation has been to provide comprehensive services for burn survivors and people with facial disfigurement in order to assist them in their physical, psychological and social rehabilitation, but also to uphold their human rights and dignity by transforming social attitudes about disfigurement through social education and advocacy. Sunshine Foundation accepts credit card donations online, bank transfers at post offices and bank counters, cash donations at its service centers, and bequest donations through written wills.

CTBC Charity Foundation[8]

(1.1% of the sample donations, 2.6% of the sample secular donations)

The CTBC Charity Foundation was established in 2004 with the support of the CTBC Group. The foundation's mission is to ensure that children from disadvantaged families can enjoy happy and fulfilling lives. The foundation designs and runs its own social programs, focusing on education and poverty. These programs include the Taiwan Dream Project, which sets up local centers to provide disadvantaged children with nutritious meals and educational support; the CTBC Poverty Alleviation Program, which offers microloans to struggling families to start businesses and escape poverty; and education aid for students and schools in need outside of Taiwan. The CTBC Charity Foundation accepts credit card donations online and via fax, as well as bank transfers through fax or mail.

Red Cross[9]

(0.8% of the sample donations, 1.8% of the sample secular donations)

The Red Cross is a global humanitarian organization dedicated to providing emergency assistance, disaster relief, and education to communities in need worldwide. Its mission includes responding to natural and man-made disasters, conducting blood do-

[8] https://www.ctbcfoundation.org.
[9] https://www.redcross.org.tw.

nation drives, offering health and safety training, supporting vulnerable populations, and delivering international aid. The Red Cross also engages in community outreach and public health initiatives to promote well-being and resilience among populations. In Taiwan, the Red Cross accepts credit card donations online or via mail/fax, bank transfers at post offices and bank counters, and cash and check donations at its local offices or by mail.

A.2 Optimal Donations without Spiritual Insurance Motive

In the model without a spiritual insurance channel, the objective function is:

$$\max_{g}(1-2p)u(\bar{I}-g)+pu(\bar{I}-g-D)+pu(\bar{I}-g+D)+\theta v(g) \tag{A.1}$$

The first order condition (FOC) is as follow:

$$-(1-2p)u'(\bar{I}-g)-pu'(\bar{I}-g-D)-pu'(\bar{I}-g+D)+\theta v'(g)=0 \tag{A.2}$$

The second order condition (SOC) is satisfied:

$$(1-2p)u''(\bar{I}-g)+pu''(\bar{I}-g-D)+pu''(\bar{I}-g+D)+\theta v''(g)<0 \tag{A.3}$$

To consider the comparative statics of optimal donations g^* with respect to expected income $\bar{I}$, rewrite g^* as $g^*(\bar{I},D)$, and denote $g^*_{\bar{I}}(\bar{I},D)=\frac{dg^*(\bar{I},D)}{d\bar{I}}$. Taking the derivative of the FOC with respect to $\bar{I}$ gives rise to the following relationship:

$$g^*_{\bar{I}}(\bar{I},D)=\frac{(1-2p)u''(\bar{I}-g)+pu''(\bar{I}-g-D)+pu''(\bar{I}-g+D)}{(1-2p)u''(\bar{I}-g)+pu''(\bar{I}-g-D)+pu''(\bar{I}-g+D)+\theta v''(g)}>0 \tag{A.4}$$

Both the numerator and the denominator are negative because the utility function u is concave. Therefore, the income effect on donations in the model without a spiritual insurance motive is positive.

Then consider the comparative statics of optimal donations g^* with respect to the size of the background risk D. Denote $g^*_D(\bar{I},D)=\frac{dg^*(\bar{I},D)}{dD}$, the derivative of the FOC with respect to D. We have the following relationship:

$$g^*_D(\bar{I},D)=\frac{pu''(\bar{I}-g+D)-pu''(\bar{I}-g-D)}{(1-2p)u''(\bar{I}-g)+pu''(\bar{I}-g-D)+pu''(\bar{I}-g+D)+\theta v''(g)}<0 \tag{A.5}$$

The denominator in (A.5) is inherited from the previous equation and is negative. The numerator in (A.5) is positive because $u''' > 0$. Therefore, the effect of the size of income uncertainty on donations in the model without a spiritual insurance motive is negative.

This ends the proof for Lemma 1, that is, in the model without a spiritual insurance motive, if expected income $\bar{I}$ rises, the optimal donation size g^* rises, and if the size of income uncertainty D rises, the optimal donation size g^* falls. In the model without a spiritual insurance motive, donation is a normal good, and shares the findings on uncertainty and consumption of normal goods in Kimball (1993).

A.3 Optimal Donations with Spiritual Insurance Motive

We next assume a spiritual insurance motive exists and derive testable implications. The objective function of the individual's optimal donation problem with a spiritual insurance motive is:

$$\max_g (1-2\bar{p})u(\bar{I}-g) + (\bar{p}-\pi(g))u(\bar{I}-g-D) + (\bar{p}+\pi(g))u(\bar{I}-g+D) + \theta v(g) \tag{A.6}$$

The FOC of the optimal donation problem is now as follows:

$$\begin{gathered}\pi'(g)[u(\bar{I}-g+D)-u(\bar{I}-g-D)] + \theta v'(g) = \\ (1-2\bar{p})u'(\bar{I}-g) + (\bar{p}-\pi(g))u'(\bar{I}-g-D) + (\bar{p}+\pi(g))u'(\bar{I}-g+D)\end{gathered} \tag{A.7}$$

On the left-hand side of (A.7), the term $\pi'(g)[u(\bar{I}-g+D)-u(\bar{I}-g-D)]$ specifically represents the (subjective) marginal benefit from spiritual insurance, and, as before, the next term $\theta v'(g)$ is the marginal benefit of donating not from spiritual insurance. The right-hand side of (A.7) is the expected marginal cost of donating g. The optimal decision balances the marginal benefits and the marginal costs of donation.

Consider an increase in the size of income uncertainty D in the above model with a spiritual insurance motive. First, the marginal benefit of donating from spiritual insurance increases because the scaling factor $u(\bar{I}-g+D)-u(\bar{I}-g-D)$ is higher. Second, the marginal cost of donating also increases through a canonical income effect, as in the model without spiritual insurance. Third, the spiritual insurance channel dampens this canonical income effect of D by shifting subjective belief from the bad state, where the income effect of D is malevolent, to the good state, where the income effect of D is benevolent. Combined, in the model with spiritual insurance, if the spiritual insurance motive is sufficiently strong—–strong enough to counterbalance the opposing income effect—–then the optimal donation g^* will increase in the size of income uncertainty D.

We formally establish the above statement in the proof below.

Proof of Proposition 1.

To initiate the proof, first examine the condition under which the second-order condition (SOC) of the optimal donation problem in the model with a spiritual insurance motive holds. Taking the second derivative of the objective function, the SOC amounts to the following condition:

$$\begin{gathered}\pi''(g)(u(\bar{I}-g+D)-u(\bar{I}-g-D))+\theta v''(g)+(1-2\bar{p})u''(\bar{I}-g)+\\(\bar{p}-\pi(g))u''(\bar{I}-g-D)+(\bar{p}+\pi(g))u''(\bar{I}-g+D)-\\2\pi'(g)\left(u'(\bar{I}-g+D)-u'(\bar{I}-g-D)\right)<0\end{gathered}\tag{A.8}$$

In Equation (A.8), all terms are negative except the final one. In an extreme scenario where this final term is dominant, the optimal donation amount would lead to what we term 'complete spiritual insurance'—effectively reducing the subjective probability of experiencing the low state to zero. This represents a corner solution in our model. However, when the subjective probability return function $\pi(\cdot)$ and/or utility function $u(\cdot)$ exhibit sufficient curvature, a different outcome emerges. This curvature ensures the satisfaction of the second-order condition, implying diminishing returns from the spiritual insurance benefits of donations. Under this more typical scenario, which we focus on henceforth, the subjective probability of the low-income state remains above zero post-donation, and the optimal donation problem adopts an interior solution.

Then, to analyze the comparative statics of optimal donation g^* with respect to expected income $\bar{I}$ and background risk D in the model with a spiritual insurance motive, we rewrite g^* as $g^*(\bar{I}, D)$, and take derivative of the FOC with respect to $\bar{I}$ and D:

$$\begin{aligned}
&g_I^*(\bar{I}, D)\left[\pi''(g)(u(\bar{I}-g+D)-u(\bar{I}-g-D))+\theta v''(g)+\right.\\
&(1-2\bar{p})u''(\bar{I}-g)+(\bar{p}-\pi(g))u''(\bar{I}-g-D)+\\
&\left.(\bar{p}+\pi(g))u''(\bar{I}-g+D)-2\pi'(g)\left(u'(\bar{I}-g+D)-u'(\bar{I}-g-D)\right)\right]\\
&=(1-2\bar{p})u''(\bar{I}-g)+(\bar{p}-\pi(g))u''(\bar{I}-g-D)+\\
&(\bar{p}+\pi(g))u''(\bar{I}-g+D)-\pi'(g)\left(u'(\bar{I}-g+D)-u'(\bar{I}-g-D)\right)
\end{aligned} \tag{A.9}$$

$$\begin{aligned}
&g_D^*(\bar{I}, D)\left[\pi''(g)(u(\bar{I}-g+D)-u(\bar{I}-g-D))+\theta v''(g)+\right.\\
&(1-2\bar{p})u''(\bar{I}-g)+(\bar{p}-\pi(g))u''(\bar{I}-g-D)+\\
&\left.(\bar{p}+\pi(g))u''(\bar{I}-g+D)-2\pi'(g)\left(u'(\bar{I}-g+D)-u'(\bar{I}-g-D)\right)\right]\\
&=-\pi'(g)\left(u'(\bar{I}-g+D)+u'(\bar{I}-g-D)\right)+\\
&(\bar{p}+\pi(g))u''(\bar{I}-g+D)-(\bar{p}-\pi(g))u''(\bar{I}-g-D)
\end{aligned} \tag{A.10}$$

Notice that the terms in the brackets on the left side of both equations are exactly the terms in the SOC. Thus, the mathematical conditions for $g_I^*(\bar{I}, D) > 0$ and $g_D^*(\bar{I}, D) > 0$ are the conditions below:

$$\begin{aligned}
&g_I^*(\bar{I}, D) > 0 \text{ if } (1-2\bar{p})u''(\bar{I}-g)+(\bar{p}-\pi(g))u''(\bar{I}-g-D)+\\
&(\bar{p}+\pi(g))u''(\bar{I}-g+D)-\pi'(g)\left(u'(\bar{I}-g+D)-u'(\bar{I}-g-D)\right)<0
\end{aligned} \tag{A.11}$$

$$\begin{aligned}
&g_D^*(\bar{I}, D) > 0 \text{ if } \pi'(g)\left(u'(\bar{I}-g+D)+u'(\bar{I}-g-D)\right)\\
&>\left(\bar{p}-\pi\left(g^*\right)\right)\left(-u''\left(\bar{I}-g^*-D\right)\right)+\left(\bar{p}+\pi\left(g^*\right)\right)u''\left(\bar{I}-g^*+D\right)
\end{aligned} \tag{A.12}$$

The condition (A.11) for $g_I^*(\bar{I}, D) > 0$ is similar to the technical requirement for the second-order condition (A.8), that is, that the spiritual insurance channel should not be so extreme that the corner case of complete spiritual insurance occurs and the conventional income effect does not exist.

More central is the condition (A.12) for $g_D^*(\bar{I}, D) > 0$, which has clear economic interpretations. On the left-hand side, $\pi'(g)(u'(\bar{I}-g+D)+u'(\bar{I}-g-D))$ is the additional benefit of donations through the spiritual insurance channel, when D increases by one, as the low-state marginal utility is now higher and the high-state marginal utility is now lower. On the right-hand side, $(\bar{p}-\pi(g^*))(-u''(\bar{I}-g^*-D))+(\bar{p}+\pi(g^*))u''(\bar{I}-g^*+D)$ is the additional increase in the expected marginal utility of foregone consumption with the increase in D, which is the income effect of higher income uncertainty that tends to reduce donations, and also exists in the model without spiritual insurance. If the left-hand side is greater than the right-hand side, that is, if the spiritual insurance channel is strong enough, the model with spiritual insurance predicts that

$$\frac{\partial g^*}{\partial D} > 0,$$

that is, when the size of income uncertainty D increases, optimal donation g^* rises. This conclusion contrasts with the model where the spiritual insurance motive is not a consideration.

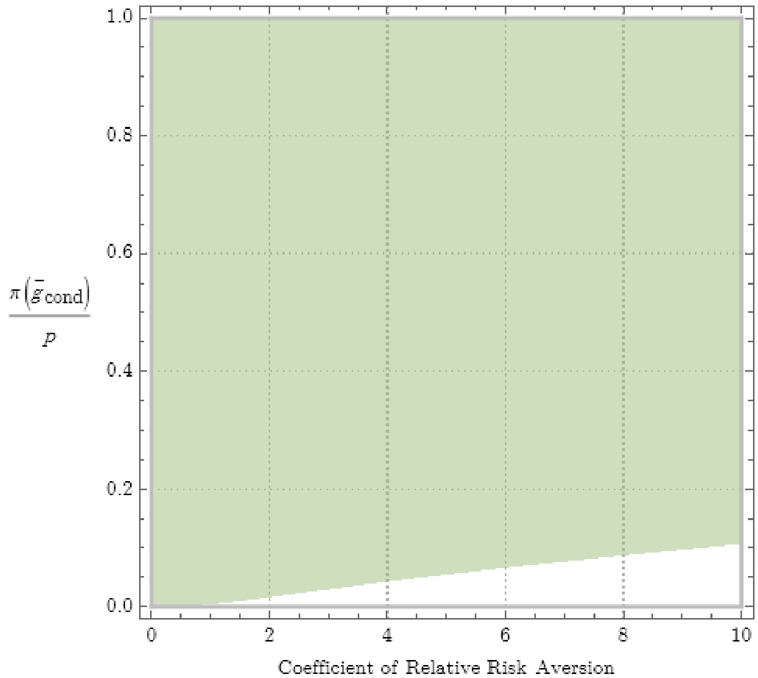
This ends the proof of Proposition 1.

The condition (A.12) that makes the spiritual insurance motive dominate is not difficult to reach. We use a numerical example to illustrate this. We choose the same functional forms as in Auriol et al. (2020). We use a constant absolute risk aversion (CARA) utility function, i.e., $u(c) = 1 - \exp\{-ac\}$. The magnitude to which the perceived probability of the bad state $\bar{p} - \pi(g)$ is reduced as an individual donates is specified as $\pi(g) = k \cdot \ln(g+1)$. The parameter k governs the relative ease with which the perceived probability is changed. We choose $\bar{I} = 10$ following Auriol et al. (2020). We choose $D = 4.27$ and $\bar{p} = 0.39$ to match the average income uncertainty of $\log$ monthly income of 0.427 in the dataset. The value of g is chosen to match the ratio of the conditional average monthly donation size to average income $(\$46/\$4067)$, which gives $g = 0.11$. We then examine whether condition (2) in the paper, that is, condition (A.12) here, holds under different values of the coefficient of absolute risk aversion a and the parameter k.

We vary the utility exponent (a) from 0 to 1.0, corresponding to a relative risk aversion (RRA) range of 0 to 10 at a mean income of $\bar{I} = 10$. Similarly, we adjust the subjective probability return coefficient k within a range that aligns the ratio of perceived probability reduction relative to the objective probability $(\pi(g)/\bar{p})$, when the donation size (g) equals the sample average, to a span of 0 to 1.0.

Figure A.1 presents our findings, showing the parameter combinations of a and k where condition (2) in the paper, that is, condition (A.12) holds true. Overall, we ob-

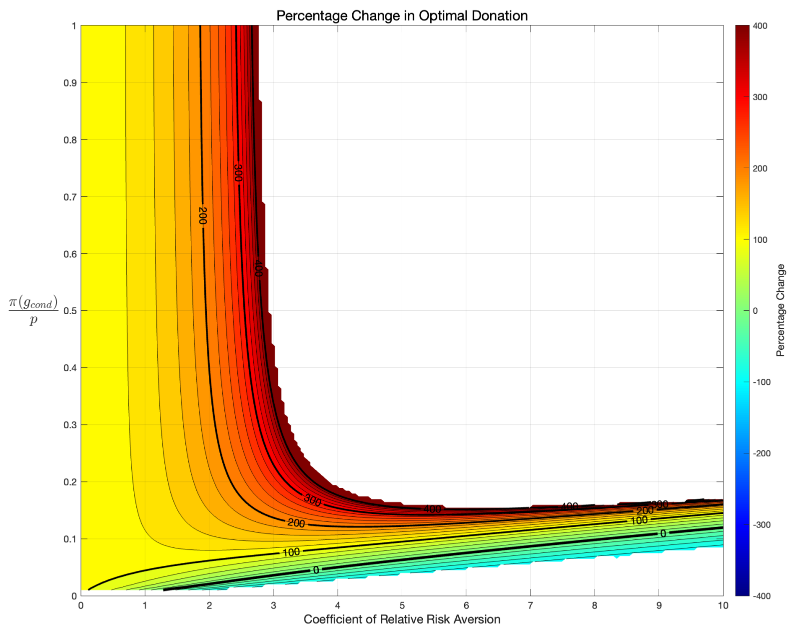
Figure A.1: Numerical Example of Parameter Ranges that Satisfy Condition (2)



serve that condition (2) is met in 94.7% of the parameter pairs examined. Notably, a higher subjective probability return coefficient (k), or a greater perceived probability reduction $(\pi(\bar{g}_{cond})/\bar{p})$, increases the likelihood of satisfying the condition. This aligns with expectations, considering that $\pi(\bar{g}_{cond})/\bar{p}$ indicates the efficacy of the spiritual insurance channel. Conversely, an increase in a reduces the probability of meeting the condition, likely due to the amplified income effect from greater income uncertainty at higher levels of risk aversion. Nevertheless, even at the highest risk aversion in our range (RRA of 10), condition (A.12) is predominantly satisfied, holding true 89.3% of the time.

Figure A.2 illustrates a related numerical exercise, where we increase income uncertainty by one standard deviation in the bank transaction data (by increasing the value of D) and visualize the resulting increase in optimal donations predicted by the model. We observe that the stronger the spiritual insurance channel—that is, a higher subjective probability return coefficient (k) or a greater perceived probability reduction $(\pi(\bar{g}_{cond})/\bar{p})$ —the larger the increase in optimal donations in response to rising income uncertainty

Figure A.2: Model Predicted Increase in Optimal Donations when Income Uncertainty Rises by 1 S.D.



(D). The empirical IV estimate of a 150-percentage-point increase in donations (95% confidence interval $[38, 262]$ percentage points) can be rationalized by the model.

This point estimate can be replicated in the model under, for example, a coefficient of relative risk aversion (RRA) of 4—corresponding to the mean risk tolerance from Barsky, Juster, Kimball, and Shapiro (1997)—and a spiritual insurance channel strength such that the average donation reduces the perceived probability of the bad state (and increases the good state)—$\pi(\bar{g}_{cond})/\bar{p}$—by approximately 10 percent of the original probability. We consider these parameter combinations to be reasonable. The 95% confidence interval of this estimate can be rationalize by, for example, (i) a RRA of 4 and a spiritual insurance channel strength such that the average donation reduces the perceived probability of the bad state (and increases the good state) by approximately 6 to 15 percent of the original probability, (ii) a RRA below 4 and a wider range of the spiritual insurance channel strength, e.g. a RRA of 3 and a $\pi(\bar{g}_{cond})/\bar{p}$ of 5 to 20 percent, or a RRA of 2 and a $\pi(\bar{g}_{cond})/\bar{p}$ above 4 percent, or (iii) a RRA above 4 and a narrower range of the spiritual insurance channel strength.

A.4 Optimal Donations with Two-Dimensional Risks

In this appendix section, we expand our model to include two distinct dimensions of risk: income risk ($\tilde{I}$) and insurable expense risk ($\tilde{E}$). As in our initial model, income risk remains uninsurable and its perceived probability distribution is modified by the spiritual insurance channel. In contrast, the expense risk, which occurs with probability q, introduces a new element as it can be hedged through market-based insurance.

Agents in our model are provided with the option to purchase a portion (α) of this market-based insurance at a cost of $\alpha(1+\lambda)qE$. This insurance compensates for a fraction (α) of the losses incurred from the expense risk. The coefficient $\lambda \geq 0$, represents the premium loading factor, a concept well-established in the insurance literature (e.g. Eeckhoudt and Schlesinger, 2013), and essentially denotes the additional cost over the expected loss that the insurance company charges for providing the coverage.

By extending the model in this manner, our objective is to explore the relationship between donations and the purchase of market-based insurance as agents navigate two types of risks—uninsurable income risk and insurable expense risk—within the same economic framework. To analyze this model relationship, we proceed to detail the agent's objective function as follows:

$$\begin{aligned}
\max_{g,\alpha} \quad & q[(1-2\bar{p})u(\bar{I}-g-(1-\alpha)E-\alpha(1+\lambda)qE) \\
& +(\bar{p}-\pi(g))u(\bar{I}-g-D-(1-\alpha)E-\alpha(1+\lambda)qE) \\
& +(\bar{p}+\pi(g))u(\bar{I}-g+D-(1-\alpha)E-\alpha(1+\lambda)qE)] \\
& +(1-q)[(1-2\bar{p})u(\bar{I}-g-\alpha(1+\lambda)qE) \\
& +(\bar{p}-\pi(g))u(\bar{I}-g-D-\alpha(1+\lambda)qE) \\
& +(\bar{p}+\pi(g))u(\bar{I}-g+D-\alpha(1+\lambda)qE)] \\
& +\theta v(g) \\
\equiv\ & \mathbb{E}_{\tilde{I}}\mathbb{E}_{\tilde{E}}u(\tilde{I}-g-(1-\alpha)\tilde{E}-\alpha(1+\lambda)qE)+\theta v(g)
\end{aligned} \tag{A.13}$$

where donation g and the purchase of market-based insurance α are the agent's two choice variables.

We obtain the following the first-order conditions for g and α, where $y_0(\alpha)$ short-hands for $\bar{I} - \alpha(1+\lambda)qE$, and $y_1(\alpha)$ short-hands for $\bar{I} - (1-\alpha)E - \alpha(1+\lambda)qE$:

$$\begin{aligned}
[g]: \quad & \pi'(g)\left\{q\left[u\left(y_1(\alpha)-g+D\right)-u\left(y_1(\alpha)-g-D\right)\right]+\right. \\
& \left.(1-q)\left[u\left(y_0(\alpha)-g+D\right)-u\left(y_0(\alpha)-g-D\right)\right]\right\}+\theta v'(g)= \\
& q\left[(\bar{p}+\pi(g))u'\left(y_1(\alpha)-g+D\right)+(\bar{p}-\pi(g))u'\left(y_1(\alpha)-g-D\right)\right. \\
& \left.+(1-2\bar{p})u'\left(y_1(\alpha)-g\right)\right]+(1-q)\left[(1-2\bar{p})u'\left(y_0(\alpha)-g\right)+\right. \\
& \left.(\bar{p}+\pi(g))u'\left(y_0(\alpha)-g+D\right)+(\bar{p}-\pi(g))u'\left(y_0(\alpha)-g-D\right)\right]
\end{aligned} \tag{A.14}$$

$$\begin{aligned}
[\alpha]: \quad & q\left(1-(1+\lambda)q\right)E\cdot\left[(1-2\bar{p})u'\left(y_1(\alpha)-g\right)\right. \\
& \left.(\bar{p}+\pi(g))u'\left(y_1(\alpha)-g+D\right)+(\bar{p}-\pi(g))u'\left(y_1(\alpha)-g-D\right)\right] \\
& =(1-q)(1+\lambda)qE\cdot\left[(1-2\bar{p})u'\left(y_0(\alpha)-g\right)\right. \\
& \left.(\bar{p}+\pi(g))u'\left(y_0(\alpha)-g+D\right)+(\bar{p}-\pi(g))u'\left(y_0(\alpha)-g-D\right)\right]
\end{aligned} \tag{A.15}$$

The FOC for g equates the spiritual insurance and non-spiritual insurance benefits of donation versus the expected utility of the forgone consumption. The FOC for α balances the marginal utilities of the claim and the non-claim states considering the premium of and compensations from the purchased insurance. Significantly, the first-order conditions for donation and the purchase of market-based insurance are interconnected via the spiritual insurance channel: donation reduces the perceived probability of the low-income state where the insurance compensation is especially beneficial, and the insurance purchase, in turn, affects the value of modifying the probability distribution of the income risk.

The second-order condition for the insurance variable α follows trivially. For the donation variable (g), the second-order condition is confirmed by substituting the term u in condition (A.8) with $\mathrm{E}_{\tilde{E}}u(\cdot)$.

Then, we conduct a comparative static analysis. This leads to the main result from the extended model with two-dimensional risks, summarized in the following proposition:

Proposition A.1 *If the spiritual insurance motive for donations is strong enough, i.e.,*

$$
\begin{aligned}
&q \cdot [1-(1+\lambda)q] \cdot \{\pi'(g)\left[u'\left(y_1(\alpha)-g-D\right)-u'\left(y_1(\alpha)-g+D\right)\right] \\
&-\left[(\bar{p}+\pi(g))(-u''\left(y_1(\alpha)-g+D\right))+(\bar{p}-\pi(g))(-u''\left(y_1(\alpha)-g-D\right))\right. \\
&\left.+(1-2\bar{p})(-u''\left(y_1(\alpha)-g\right))\right]\} \\
&-(1-q) \cdot [(1+\lambda)q] \cdot \{\pi'(g)\left[u'\left(y_0(\alpha)-g-D\right)-u'\left(y_0(\alpha)-g+D\right)\right] \\
&-\left[(\bar{p}+\pi(g))(-u''\left(y_0(\alpha)-g+D\right))+(\bar{p}-\pi(g))(-u''\left(y_0(\alpha)-g-D\right))\right. \\
&\left.+(1-2\bar{p})(-u''\left(y_0(\alpha)-g\right))\right]\}>0
\end{aligned}
\tag{A.16}
$$

then donation g and insurance purchase α are negatively related, that is

$$
\frac{\partial g^*}{\partial \alpha}<0, \frac{\partial \alpha^*}{\partial g}<0
$$

Proof of Proposition A.1.

Consider rewriting g^* as $g^*(\alpha)$. Upon differentiating (A.14) with respect to α, we obtain the following arithmetically tedious but straightforward relationship:

$$
\begin{aligned}
&g_\alpha^*\{(1-2\bar{p})\left[qu''\left(y_1(\alpha)-g\right)+(1-q)u''\left(y_0(\alpha)-g\right)\right] \\
&+(\bar{p}+\pi(g))\left[qu''\left(y_1(\alpha)-g+D\right)+(1-q)u''\left(y_0(\alpha)-g+D\right)\right] \\
&+(\bar{p}-\pi(g))\left[qu''\left(y_1(\alpha)-g-D\right)+(1-q)u''\left(y_0(\alpha)-g-D\right)\right] \\
&-2\pi'(g)\left[qu'\left(y_1(\alpha)-g+D\right)+(1-q)u'\left(y_0(\alpha)-g+D\right)\right. \\
&\left.-qu'\left(y_1(\alpha)-g-D\right)-(1-q)u'\left(y_0(\alpha)-g-D\right)\right]+ \\
&\pi''(g)\left[qu\left(y_1(\alpha)-g+D\right)+(1-q)u\left(y_0(\alpha)-g+D\right)\right. \\
&\left.-qu\left(y_1(\alpha)-g-D\right)-(1-q)u\left(y_0(\alpha)-g-D\right)\right]+\theta v''(g)\} \\
&=q \cdot [1-(1+\lambda)q] \cdot E \cdot \{\pi'(g)\left[u'\left(y_1(\alpha)-g-D\right)-u'\left(y_1(\alpha)-g+D\right)\right] \\
&-(\bar{p}+\pi(g))(-u''\left(y_1(\alpha)-g+D\right))-(\bar{p}-\pi(g))(-u''\left(y_1(\alpha)-g-D\right)) \\
&-(1-2\bar{p})(-u''\left(y_1(\alpha)-g\right))\} \\
&-(1-q) \cdot [(1+\lambda)q] \cdot E \cdot \{\pi'(g)\left[u'\left(y_0(\alpha)-g-D\right)-u'\left(y_0(\alpha)-g+D\right)\right] \\
&-(\bar{p}+\pi(g))(-u''\left(y_0(\alpha)-g+D\right))-(\bar{p}-\pi(g))(-u''\left(y_0(\alpha)-g-D\right)) \\
&-(1-2\bar{p})(-u''\left(y_0(\alpha)-g\right))\}
\end{aligned}
\tag{A.17}
$$

The expressions within the curly brackets on the left-hand side precisely match those in the second-order condition for g, thereby being less than zero. To establish $\frac{\partial g^*}{\partial \alpha}<0$, it is sufficient for the right-hand side of this equation to be greater than zero, a condition that given $qE > 0$ is equivalent to condition (A.16).

In a similar vein, let us denote $\alpha_g^* = \frac{\partial \alpha^*}{\partial g}$ and differentiate (A.14) with respect to g:

$$\begin{gathered}
\alpha_g^* \{[1-(1+\lambda)q]^2 qE \cdot [(1-2\bar{p})u''(y_1(\alpha)-g) \\
+(\bar{p}+\pi(g))u''(y_1(\alpha)-g+D)+(\bar{p}-\pi(g))u''(y_1(\alpha)-g-D)] \\
-[(1+\lambda)q]^2(1-q)E \cdot [(1-2\bar{p})u''(y_0(\alpha)-g) \\
+(\bar{p}+\pi(g))u''(y_0(\alpha)-g+D)+(\bar{p}-\pi(g))u''(y_0(\alpha)-g-D)]\} \\
= q \cdot [1-(1+\lambda)q] \cdot E \cdot \{\pi'(g)[u'(y_1(\alpha)-g-D)-u'(y_1(\alpha)-g+D)] \\
-(\bar{p}+\pi(g))(-u''(y_1(\alpha)-g+D))-(\bar{p}-\pi(g))(-u''(y_1(\alpha)-g-D)) \\
-(1-2\bar{p})(-u''(y_1(\alpha)-g))\} \\
-(1-q) \cdot [(1+\lambda)q] \cdot E \cdot \{\pi'(g)[u'(y_0(\alpha)-g-D)-u'(y_0(\alpha)-g+D)] \\
-(\bar{p}+\pi(g))(-u''(y_0(\alpha)-g+D))-(\bar{p}-\pi(g))(-u''(y_0(\alpha)-g-D)) \\
-(1-2\bar{p})(-u''(y_0(\alpha)-g))\}
\end{gathered} \tag{A.18}$$

Similarly, the expressions within the brackets on the left-hand side correspond to those in the SOC for α, collectively summing to less than zero. Notably, the right-hand side of this equation mirrors that of the preceding one. As a result, condition (A.16) is sufficient to ensure $\frac{\partial \alpha^*}{\partial g} < 0$. This concludes the proof of Proposition A.1.

The remaining aspect of Proposition A.1 is to explain how condition (A.16), which establishes substitutability between donation and market-based insurance, requires a sufficiently strong spiritual insurance channel.

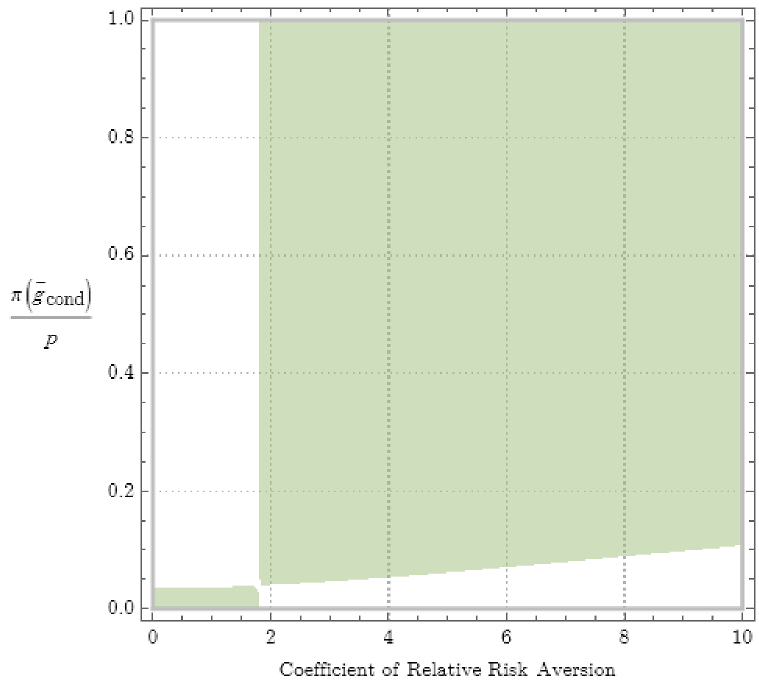
Donating g affects the cost-benefit analysis of insurance purchase α in the model in four specific ways. First, through the spiritual insurance channel, donating g reduces the subjective probability of the low-income state, increases the subjective probability of the high-income state, and reduces the expected marginal utility benefit to buying insurance in the claim states (row 1 of condition (A.16)). Second, spending g reduces money at hand in all states—akin to the income effect in condition (2)—and increases the benefit of insurance in the claim states (rows 2 and 3 of condition (A.16)). Third, reducing the subjective probability of the low-income state and increasing the subjective probability of the high-income state also reduces the expected marginal utility cost of paying the insurance premium in the non-claim states (row 4 of condition (A.16)). Fourth and last, spending g reduces money at hand in all states and increases the marginal utility cost of paying the insurance premium in the non-claim states (rows 5 and 6 of condition (A.16)).

Condition (A.16) thus first requires a strong enough spiritual insurance channel that dominates the canonical income effect in the claim states so that the net effects of row 1–3 are positive. This requirement closely resembles condition (2). Condition (A.16) further requires that the net effect of the spiritual insurance channel is higher in the claim states than in the non-claim states, which is natural given that the optimal insurance coverage is partial in the model and $u'' < 0$. In this case, the net effects in rows 1–3 dominate the net effects in rows 4–6, leading to condition (A.16) being satisfied, and donations and insurance coverage are substitutes. Alternatively, if the spiritual insurance channel is weak or absent, the relationship between donations and the purchase of insurance is reversed.

To illustrate the conditions under which donations and market-based insurance become substitutes, we conduct a numerical exercise similar to that in Section A.2. We maintain the same CARA utility function $u(c) = 1 - \exp\{-ac\}$ and probability reduction function $\pi(g) = k \cdot \ln(g+1)$, with mean income $\bar{I} = 10$ and income uncertainty $D = 4.27$. For the new parameters related to expense risk, we set the probability of expense shock $q = 0.3$, the size of expense risk $E = 0.5\bar{I}$, the insurance loading factor $\lambda = 0.2$, and the insurance coverage ratio $\alpha = 0.7$. These values reflect relatively infrequent but substantial expense shocks with partial insurance coverage at a moderate loading cost.

Figure A.3 presents parameter combinations of risk aversion (a) and relative probability reduction $(\pi(g)/p)$ where condition (A.16) holds, indicating regions where donations and market-based insurance act as substitutes. The shaded area shows where the spiritual insurance effect is strong enough to dominate the income effect, making donations and insurance coverage strategic substitutes. Our numerical analysis reveals that condition (A.16) is satisfied in approximately 76.7% of the parameter space exam-

Figure A.3: Parameter Combinations Where Condition (A.16) Holds

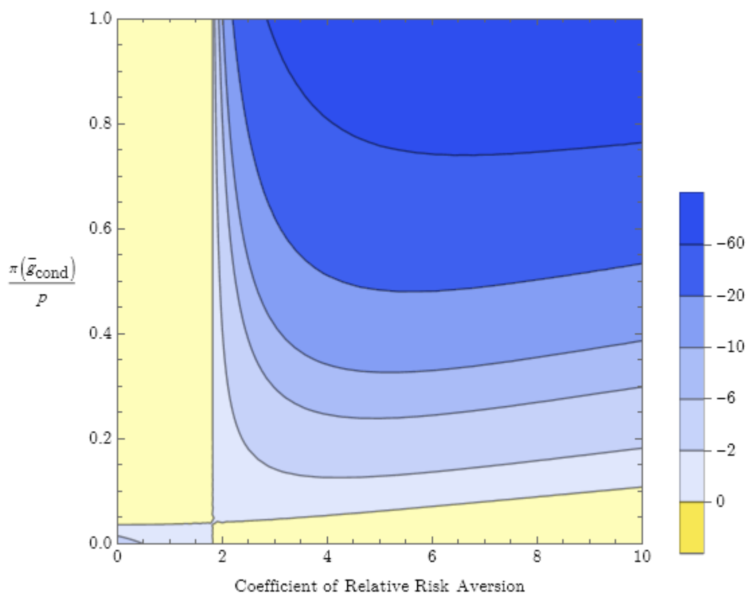


ined. Notably, the condition holds primarily when individuals have a sufficiently strong spiritual insurance motive and are sufficiently risk-averse, which is consistent with the interpretation that spiritual insurance serves as a psychological hedge against risk.

Figure A.4 shows that the model establishes a correspondence between the change in insurance expenditures for a \$1 increase in donations and various parameter combinations. This allows us to place our empirical estimates within a theoretical context. Our empirical estimate shows an approximate \$4 reduction in insurance expenditures (95% confidence interval $[\$0 - \$8]$) for every \$1 increase in donations. This point estimate can be replicated in the model under certain parameter combinations, such as with a coefficient of relative risk aversion (RRA) of 4—corresponding to the mean risk tolerance from Barsky, Juster, Kimball, and Shapiro (1997)—and a spiritual insurance channel strength such that the average donation reduces the perceived probability of the bad state (and increases the good state) by approximately one-fifth of the original probability. The 95% confidence interval of this estimate can be rationalize by, for example, a RRA above 1.8 and a spiritual insurance channel strength such that the average donation reduces the perceived probability of the bad state (and increases the good state) by approximately 5 to 30 percent of the original probability. We consider these parameter combinations to be reasonable.

This result supports our theoretical prediction that when the spiritual insurance motive is sufficiently strong, individuals may view religious donations and conventional insurance as alternative means of managing risk broadly defined.

Figure A.4: The Model Predicted Change in Insurance Expenditures with a $1 Increase in Donation



A.5 Optimal Donations with Increased Altruism Motive

In this appendix section, we discuss the prediction of an increased altruism motive—characterized by a tendency towards more altruistic acts in adverse or uncertain situations—on donation behavior and on the interplay between donations and insurance purchases.

We proceed with this discussion by including in the plain vanilla initial model without a spiritual insurance motive a warm-glow weight $\theta(D)$ that increases with the size of income uncertainty D. This variable warm-glow weight reflects an increased altruism motive. The agent's objective function is now:

$$\max_g (1-2p)u(\bar{I}-g) + pu(\bar{I}-g-D) + pu(\bar{I}-g+D) + \theta(D)v(g) \tag{A.19}$$

We assume that $\theta'(D) > 0$ and $\theta''(D) \leq 0$.

It is straight forward to show that $g_I^*(\bar{I}, D) > 0$ in this model, so that optimal donations increase with expected income $\bar{I}$. The relationship between optimal donations and the size of income uncertainty D is as follows:

$$g_D^*(\bar{I}, D) = \frac{pu''(\bar{I}-g+D) - pu''(\bar{I}-g-D) - \theta'(D)v'(g)}{(1-2p)u''(\bar{I}-g) + pu''(\bar{I}-g-D) + pu''(\bar{I}-g+D) + \theta(D)v''(g)} \tag{A.20}$$

With a strong enough increased altruism motive, optimal donations g^* increase with the size of income uncertainty D. The denominator is negative because u is concave. In the numerator, if $\theta'(D)$ is large enough, then the increased altruism motive dominates the income effect, represented by the first two terms in the numerator (which combine to be positive because of positive prudence, $u''' > 0$), and results in a negative numerator.

Hence, the empirical finding that higher income uncertainty is observed with more donations is consistent with both the model with a spiritual insurance motive and the model with an increased altruism motive.

However, if we consider the two-dimensional risks situation, things are different. $\frac{\partial g^*}{\partial \alpha}$ and $\frac{\partial \alpha}{\partial g^*}$ in the model with just the increase altruism motive but augmented with two-dimensional risks are determined as follows:

$$\begin{aligned}
& g_\alpha^* \{(1-2\bar{p})\left[qu''\left(y_1(\alpha)-g\right) + (1-q)u''\left(y_0(\alpha)-g\right)\right] \\
& +\bar{p}\left[qu''\left(y_1(\alpha)-g+D\right) + (1-q)u''\left(y_0(\alpha)-g+D\right)\right] \\
& +\bar{p}\left[qu''\left(y_1(\alpha)-g-D\right) + (1-q)u''\left(y_0(\alpha)-g-D\right)\right] + \theta(D)v''(g)\} \\
& = q\cdot[1-(1+\lambda)q]\cdot E\cdot\{\bar{p}u''\left(y_1(\alpha)-g+D\right) + \bar{p}u''\left(y_1(\alpha)-g-D\right) \\
& +(1-2\bar{p})u''\left(y_1(\alpha)-g\right)\} - (1-q)\cdot[(1+\lambda)q]\cdot E\cdot\{\bar{p}u''\left(y_0(\alpha)-g+D\right) \\
& +\bar{p}u''\left(y_0(\alpha)-g-D\right) + (1-2\bar{p})u''\left(y_0(\alpha)-g\right)\}
\end{aligned} \tag{A.21}$$

$$
\begin{aligned}
&\alpha_g^* \{[1-(1+\lambda)q]^2 qE \cdot [(1-2\bar{p})u''(y_1(\alpha)-g)+\bar{p}u''(y_1(\alpha)-g+D) \\
&+\bar{p}u''(y_1(\alpha)-g-D)] - [(1+\lambda)q]^2(1-q)E \cdot [(1-2\bar{p})u''(y_0(\alpha)-g) \\
&+\bar{p}u''(y_0(\alpha)-g+D)+\bar{p}u''(y_0(\alpha)-g-D)]\} \\
&= q \cdot [1-(1+\lambda)q] \cdot E \cdot \{\bar{p}u''(y_1(\alpha)-g+D)+\bar{p}u''(y_1(\alpha)-g-D) \\
&+(1-2\bar{p})u''(y_1(\alpha)-g)\} - (1-q) \cdot [(1+\lambda)q] \cdot E \cdot \{\bar{p}u''(y_0(\alpha)-g+D) \\
&+\bar{p}u''(y_0(\alpha)-g-D)+(1-2\bar{p})u''(y_0(\alpha)-g)\}
\end{aligned}
\tag{A.22}
$$

The terms within the curly brackets on the left-hand sides of the above equations are negative, aligning with the respective SOCs. The right-hand side, shared by both equations, tends to be negative because $u''' > 0$ and $y_1(\alpha) < y_0(\alpha)$. Consequently, $\frac{\partial g^*}{\partial \alpha}$ and $\frac{\partial \alpha}{\partial g^*}$ tend to be positive. Intuitively, insurance coverage, in this context, does not directly influence $\theta(D)$, thus not diminishing the altruistic donation motive. Instead, it facilitates better consumption smoothing, allowing agents to donate more ex-ante. Conversely, ex-ante donating more reduces the economic resource at hand in expense states and increases the demand for insurance. This dynamic makes insurance purchase and donation complements, rather than substitutes, in the model solely influenced by the increased altruism motive.

A.6 Multiple Hypothesis Testing

Motivated by the observation that donors to religious organizations more frequently state a "seeking blessings" motive (Figure 1), we have compared the degrees to which spiritual insurance predictions manifest in religious versus secular donation behaviors in multiple ways. That is, we have analyzed the difference in the predictive effects of income uncertainty on religious and secular donations, the difference in the predictive effects of health shocks on these donations, as well as difference in the associations between making these donations and insurance purchasing.

A statistical risk that arises when we test for differences in religious versus secular donation behaviors in multiple ways is that of false positives due to multiple hypothesis testing (e.g. Romano and Wolf, 2005, List, Shaikh, and Xu, 2019; List, Shaikh, and Vayalinkal, 2023). We adjust the p-values for multiple hypothesis testing using the stringent Romano and Wolf (2005) bootstrap procedure that accounts for the dependence structure among the tests, and report the results in Table A.5.

[Table A.5 here]

The adjusted p-values that address multiple hypothesis testing maintain the same statistical significance of the religious versus secular donation comparisons observed in the baseline estimations. Specifically, for the income uncertainty effects, the unadjusted (adjusted) p-values are 0.000 (0.004) for the likelihood to donate and 0.026 (0.049) for the donation amount, both significantly different at the 1% and 5% levels, respectively. For health shock effects, the unadjusted (adjusted) p-values are 0.000 (0.002) for both the likelihood to donate and the donation amount, significantly different at the 1% level. For the negative association between donation and insurance purchasing, comparing religious donations and secular donations, the coefficient difference tests yield unadjusted (adjusted) p-values of 0.186 (0.213) for the incidence of donation and 0.186 (0.249) for the donation amount, slightly above the threshold for statistically significant difference. Notably and consistently, the coefficient difference point estimates indicate stronger effects for religious donations in response to income uncertainty (0.23% for probability, 0.11 for amount) and health shocks (2.30% for probability, 1.87 for amount), while religious donations appear more negatively associated with insurance purchases than secular donations (-45.13 for probability, -3.74 for amount). Collectively, these results suggest a rejection of the joint hypothesis that the manifestation of spiritual insurance predictions is equivalent between religious and secular donation behaviors.

Furthermore, we also apply this testing framework to examine whether the effects of income uncertainty differ depending on the direction of the shock (positive versus negative). Table A.6 reports the results for tests comparing the coefficients on positive and negative income uncertainty across donation and insurance outcomes. For donation behaviors, the adjusted p-values suggest statistical evidence for differences is weaker after adjustment. Specifically, for religious donation probability, the unadjusted (adjusted) p-values are 0.081 (0.121), and for religious donation amount, they are 0.118 (0.162). Similar patterns are observed for secular donations. Nevertheless, for insurance-related behaviors, the statistical evidence for differences is robust. The unadjusted (adjusted p-values for the predictive effect of uncertainty on insurance purchase are 0.000 (0.001),and for the sensitivity change with donation in the income uncertainty and insurance expenditure relationship, they are 0.037 (0.058).

[Table A.6 here]

References for Online Appendix

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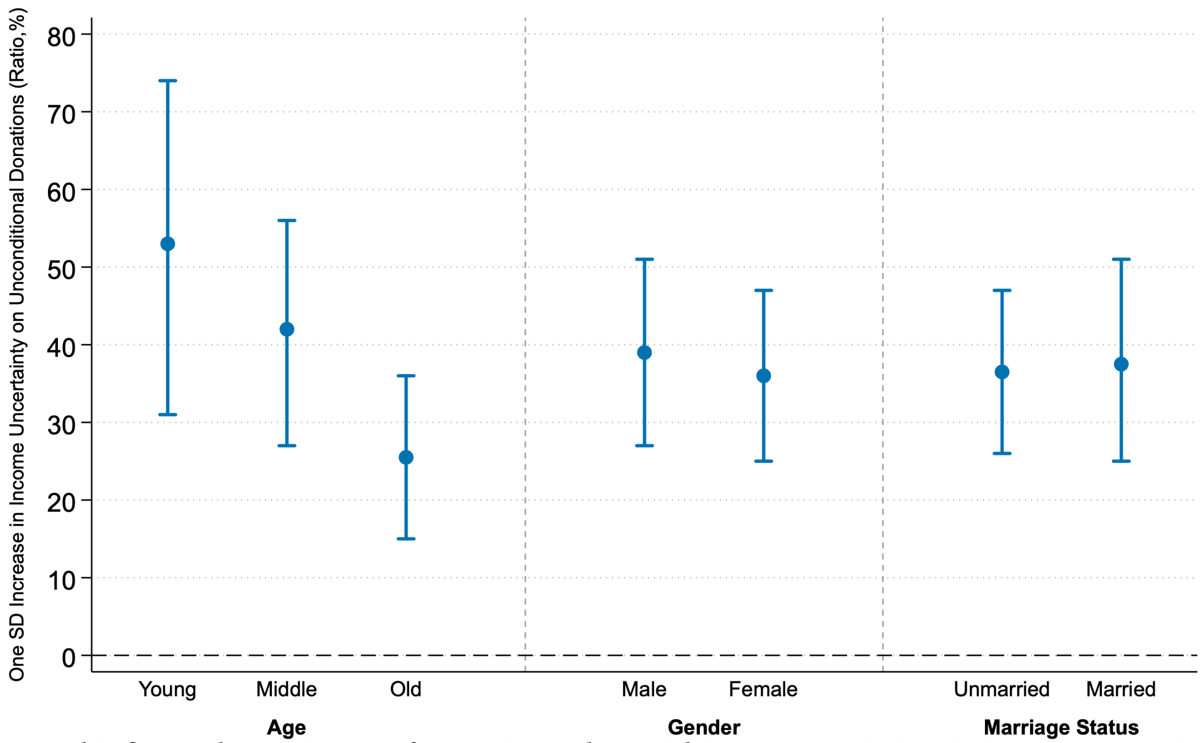
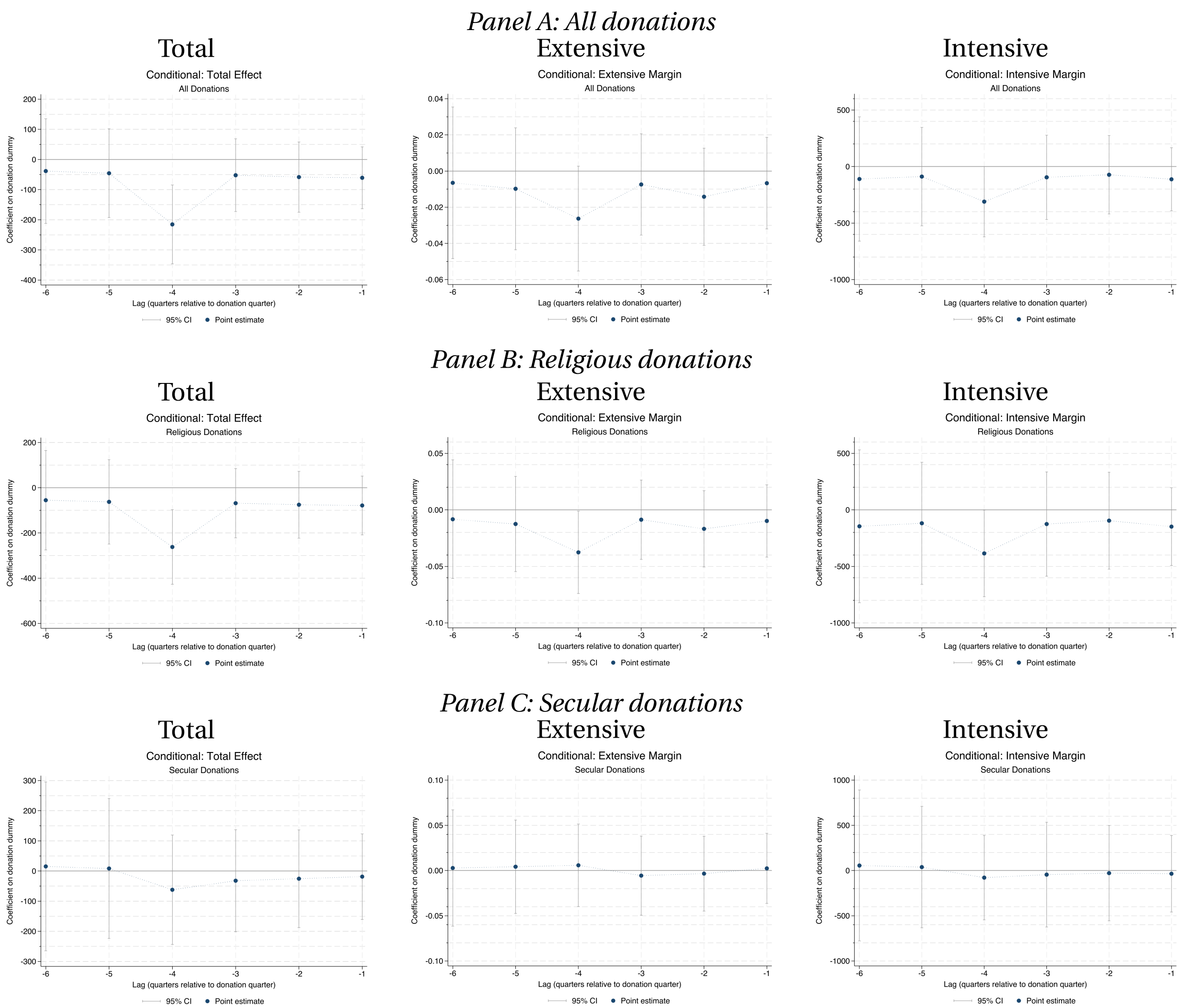
B. Appendix Tables and Additional Figures

Figure A.5: Income Uncertainty Predicts Donations
(Heterogeneity Across Demographics)



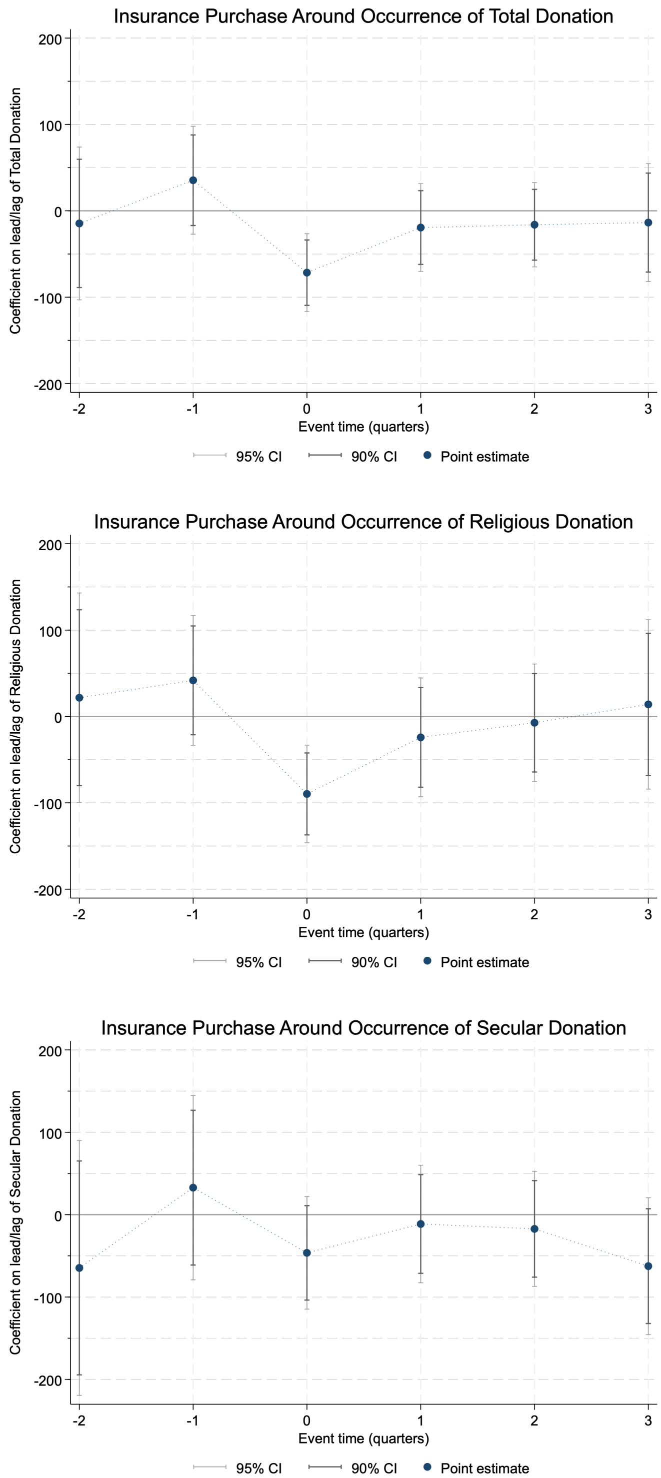
Notes: This figure plots estimates of regressions where within-person variations in income uncertainty predict donations, where we split the bank transaction sample into subsamples by demographic groups. The dependent variable is the next-quarter donation amount. The main independent variable of interest, income uncertainty, is the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters. Control variables are log income, log financial wealth, and demographic variables that include age, age squared, education, occupation, marital status, and number of dependents. For each subsample, we plot the ratio of the predicted change (positive means increase) in the next-quarter donation amount when income uncertainty experienced in the recent past rise by one sample standard deviation, divided by the subsample average amount of quarterly donations. Standard errors are clustered at the individual level. 95% confidence intervals are plotted as well as the point estimates.

Figure A.6: Insurance Renewal Cycle Analysis: Substitution Coefficients by Lag Between Donation and Most Recent Insurance Purchase ($k = -6, \ldots, -1$; $k = -4$ = four quarters earlier, the annual-renewal window)



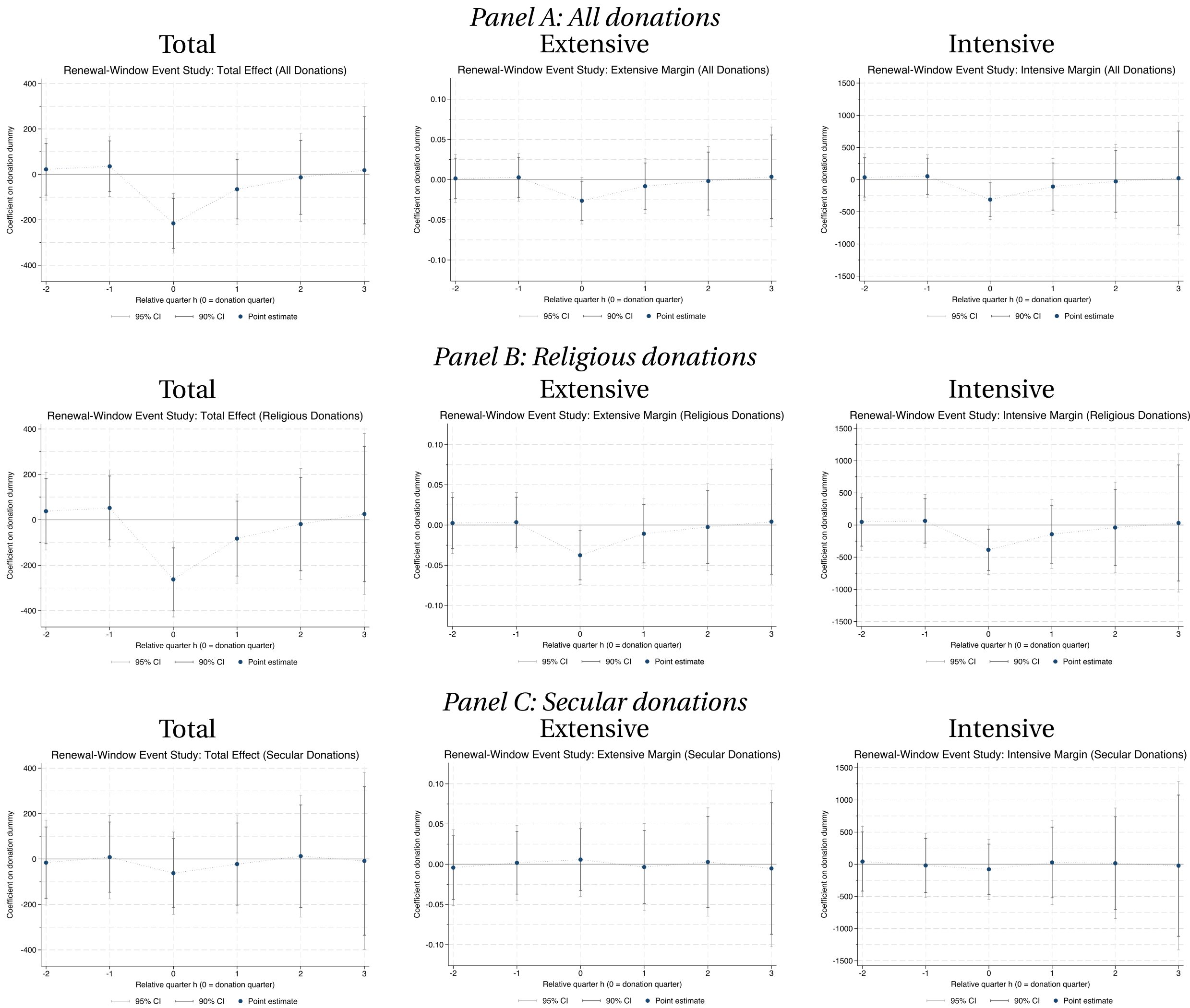
Notes: The figure reports the coefficient on the donation dummy in a separate regression estimated for each lag $k \in \{-6, \ldots, -1\}$, where the sample in each regression is restricted to prior purchasers whose most recent observed insurance transaction occurred exactly $|k|$ quarters before the donation quarter. The dependent variable is quarterly insurance spending in dollars (Total), an indicator for any insurance purchase (Extensive), or insurance spending conditional on purchase (Intensive). Each specification includes individual fixed effects, city$\times$quarter fixed effects, income uncertainty, and baseline demographic and financial controls (same controls as Table 5). Standard errors are clustered at the individual level. Filled circles are point estimates; thin vertical lines are 95% confidence intervals. The religious panel shows a sharp spike at $k = -4$ on all three margins, with adjacent $k = -3$ and $k = -5$ small and insignificant. The secular panel is flat at every lag, confirming the pattern is religious-specific.

Figure A.7: Insurance Purchase Dynamics Around the Donation Event



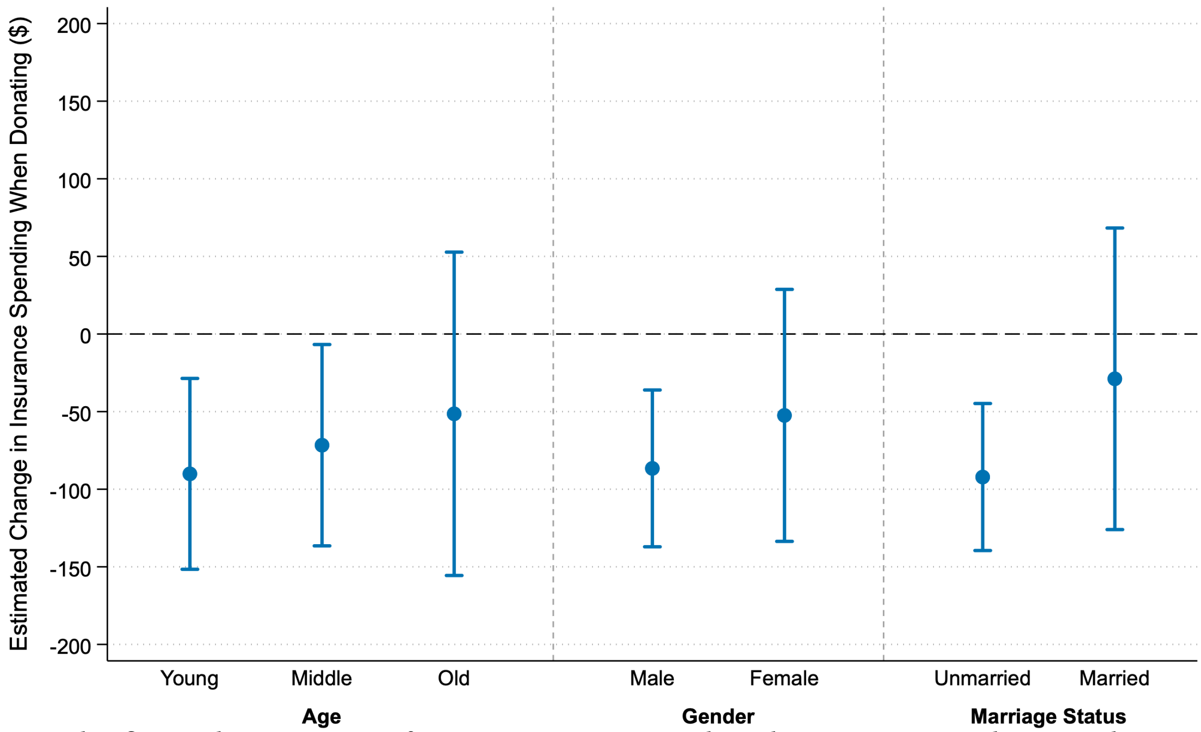
Notes: This figure reports event-study coefficients from estimating the donation–insurance substitution specification on the whole sample. We estimate a separate regression for each quarter $h \in \{-2, \ldots, +3\}$ relative to the donation quarter, where the dependent variable is insurance expenditure in quarter h and the independent variable is the quarter-0 donation dummy. The top, middle, and bottom panels report results for Total Donations, Religious Donations, and Secular Donations, respectively. Each specification includes individual fixed effects, city×quarter fixed effects, income uncertainty, and baseline demographic and financial controls (same controls as Table 5). Standard errors are clustered at the individual level. Filled circles are point estimates; gray bars are 90% confidence intervals and thin vertical lines are 95% confidence intervals.

Figure A.8: Event Study for the Up-for-Renewal Prior Purchasers ($h = -2, \ldots, +3$ traced for the Prior$_{k4}$ Subsample)



Notes: This figure reports event-study coefficients from estimating the donation–insurance substitution specification on the Prior$_{k4}$ subsample (individuals whose most recent observed insurance transaction was exactly four quarters before the donation quarter, the plausible annual-renewal window). For each event time $h \in \{-2, -1, 0, +1, +2, +3\}$ relative to the donation quarter, the plotted coefficient is the per-quarter effect of the donation dummy on the margin indicated in the column (Total: quarterly insurance spending in dollars; Extensive: indicator for any purchase; Intensive: spending conditional on purchase). Coefficients are *not* cumulative: each estimate captures the effect in that single horizon alone. Each specification includes individual fixed effects, city×quarter fixed effects, income uncertainty, and baseline demographic and financial controls (same controls as Table 5). Standard errors are clustered at the individual level. Filled circles are point estimates; thin vertical lines are 95% confidence intervals.

Figure A.9: Heterogeneity in the Substitution Pattern Between Donations and Insurance



Notes: This figure plots estimates of regressions examining the substitution pattern between donations and insurance, where we split the sample into subsamples by demographic groups (Age, Gender, and Marital Status). The dependent variable is quarterly insurance spending ($). The main independent variable of interest is an indicator variable equal to one if a donation was made in the quarter and zero otherwise. Each specification includes individual fixed effects, city×quarter fixed effects, income uncertainty, and baseline demographic and financial controls (same controls as Table 5). For each subsample, we plot the point estimate representing the estimated change in quarterly insurance spending (negative means decrease) when a donation occurs, relative to the no-donation baseline. Standard errors are clustered at the individual level. 95% confidence intervals are plotted as well as the point estimates.

Table A.1: Variable Definitions: Bank Transaction Dataset

Variable	Definition
Dependent Variables	
Donation amount$_{t+1}$	Total amount donated by individual in quarter $t+1$ (USD)
Religious donation$_{t+1}$	Amount donated to philanthropic foundations connected with a religion or spiritual tradition in quarter $t+1$ (USD)
Secular donation$_{t+1}$	Amount donated to secular philanthropic foundations in quarter $t+1$ (USD)
Pr(donation$_{t+1}$)	Dummy variable equal to 1 if individual makes any donation in quarter $t+1$, 0 otherwise
Insurance expenditures$_{t+1}$	Total amount spent on life insurance and private health insurance in quarter $t+1$ (USD)
Main Independent Variables	
Income uncertainty$_t$ ($\hat{\sigma}_{i,t}$)	Standard deviation of unpredicted component of log monthly payroll income over preceding four quarters
Positive uncertainty$_t$ ($\hat{\sigma}^{pos}_{i,t}$)	Semi-deviation of income uncertainty, calculated using only the positive residual income shocks
Negative uncertainty$_t$ ($\hat{\sigma}^{neg}_{i,t}$)	Semi-deviation of income uncertainty, calculated using only the negative residual income shocks
Health shock occurrence$_t$	Dummy variable equal to 1 if medical expenditures in quarter t exceed the sample's positive median, 0 otherwise
Health shock amount$_t$	Amount of above-median medical expenditures in quarter t (USD)
Control Variables	
Income$_t$	Average monthly payroll income during quarter t (log USD)
Financial wealth$_t$	Sum of value of savings, bonds, funds, and stocks net of debt, at the end of the quarter (log USD)
Age	Individual's age in years
Age squared	Square of individual's age
Female	Dummy variable equal to 1 if individual is female, 0 otherwise

Married	Dummy variable equal to 1 if individual is married, 0 otherwise
Education (baseline: Graduate school and above)	
Undergraduate	Dummy variable equal to 1 if highest education is undergraduate degree
Vocational school	Dummy variable equal to 1 if highest education is vocational school
High school and below	Dummy variable equal to 1 if highest education is high school or below
Occupation (baseline: Public sector officers)	
Agricultural workers	Dummy variable equal to 1 if occupation is agricultural worker
Blue-collar workers	Dummy variable equal to 1 if occupation is blue-collar worker
White-collar workers	Dummy variable equal to 1 if occupation is white-collar worker
Service-sector workers	Dummy variable equal to 1 if occupation is service-sector worker
Owner-managers	Dummy variable equal to 1 if occupation is owner-manager
Executives	Dummy variable equal to 1 if occupation is executive
Others	Dummy variable equal to 1 if occupation is other category
Dependents (baseline: No dependent)	
One dependent	Dummy variable equal to 1 if individual has one dependent
Two dependents	Dummy variable equal to 1 if individual has two dependents
More than two dependents	Dummy variable equal to 1 if individual has more than two dependents

Notes: This table provides definitions for all variables used in the analysis of the bank transaction dataset. The sample consists of 74,023 individuals over 8 quarters (July 2013 through June 2015), resulting in 592,184 individual-quarter observations. All monetary amounts are converted to USD at the prevailing exchange rate. Income uncertainty measures are computed using residualized log monthly income after removing predictable components through regression on demographic characteristics and time fixed effects.

Table A.2: Income Uncertainty Predicts Donation
(Full set of control coefficients)

Panel A: Probability of donation ($t+1$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Pr(donation$_{t+1}$)			
Specification	OLS	OLS	OLS	IV	IV	IV
Income uncertainty$_t$	0.70%***	0.70%***	0.70%***	1.86%***	1.92%***	1.90%***
	(0.06%)	(0.06%)	(0.06%)	(0.56%)	(0.59%)	(0.60%)
Income$_t$		-0.02%	0.02%		0.07%	0.07%
		(0.03%)	(0.03%)		(0.05%)	(0.06%)
Financial wealth$_t$		0.02	0.02		0.01	0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Age squared		-0.01**	-0.01**		-0.00	-0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Married		0.06	0.04		0.17	0.14
		(0.35)	(0.35)		(0.38)	(0.38)
Education (baseline: Graduate school and above)						
Undergraduate		-0.67	-0.66		-0.57	-0.55
		(0.70)	(0.71)		(0.72)	(0.72)
Vocational school		-0.48	-0.48		-0.32	-0.31
		(0.79)	(0.79)		(0.80)	(0.80)
High school and below		-0.78	-0.78		-0.49	-0.48
		(0.77)	(0.77)		(0.75)	(0.75)
Occupation (baseline: Public sector officers)						
Agricultural workers		0.24	0.56		0.67	1.04
		(1.18)	(1.21)		(1.43)	(1.47)
Blue-collar workers		0.12	0.15		-0.16	-0.14
		(1.04)	(1.04)		(1.25)	(1.25)
White-collar workers		-0.06	-0.04		-0.35	-0.33
		(1.06)	(1.06)		(1.26)	(1.26)
Service-sector workers		-0.11	-0.10		-0.45	-0.44
		(1.18)	(1.18)		(1.37)	(1.37)
Owner-managers		0.60	0.62		0.37	0.38
		(1.37)	(1.37)		(1.58)	(1.58)
Executives		1.05	1.07		0.89	0.90
		(1.16)	(1.16)		(1.36)	(1.36)
Others		0.50	0.52		0.22	0.26
		(1.06)	(1.06)		(1.27)	(1.27)
Dependents (baseline: No dependent)						
One dependent		-1.10	-1.09		-1.33	-1.32
		(0.86)	(0.86)		(0.95)	(0.95)
Two dependents		-0.94	-0.91		-1.77*	-1.73
		(1.02)	(1.02)		(1.07)	(1.07)
More than two dependents		-1.82	-1.81		-0.72	-0.74
		(1.25)	(1.25)		(0.70)	(0.70)
Constant	1.74***	10.05**	10.28**			
	(0.00)	(4.02)	(4.02)			
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	403.0	394.0	378.8
R^2-Adjusted	0.384	0.384	0.384	/	/	/

Mean Pr(Donation$_{t+1}$)	1.46%	1.46%	1.46%	1.46%	1.46%	1.46%
Cond. Mean(Dona. Amt$_{t+1}$)	\$97.10	\$97.10	\$97.10	\$97.10	\$97.10	\$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES

Panel B: Donation amount ($t+1$)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Donation amount$_{t+1}$			
Specification	OLS	OLS	OLS	IV	IV	IV
Income uncertainty$_t$	0.53***	0.52***	0.52***	2.09***	2.17***	2.13***
	(0.06)	(0.06)	(0.06)	(0.77)	(0.81)	(0.83)
Income$_t$		0.01	0.02		0.12*	0.12
		(0.06)	(0.06)		(0.07)	(0.07)
Financial wealth$_t$		0.04*	0.04*		0.02	0.02
		(0.02)	(0.02)		(0.02)	(0.02)
Age squared		-0.01**	-0.01**		-0.01*	-0.01*
		(0.00)	(0.00)		(0.00)	(0.00)
Married		0.17	0.16		0.28	0.26
		(0.29)	(0.29)		(0.30)	(0.30)
Education (baseline: Graduate school and above)						
Undergraduate		-0.71	-0.71		-0.50	-0.49
		(0.56)	(0.56)		(0.57)	(0.57)
Vocational school		-0.30	-0.29		0.04	0.04
		(0.65)	(0.65)		(0.65)	(0.65)
High school and below		-0.84	-0.83		-0.40	-0.40
		(0.62)	(0.63)		(0.60)	(0.60)
Occupation (baseline: Public sector officers)						
Agricultural workers		0.34	0.62		0.73	1.09
		(0.89)	(0.91)		(1.11)	(1.15)
Blue-collar workers		0.12	0.14		-0.16	-0.15
		(0.74)	(0.74)		(0.91)	(0.91)
White-collar workers		-0.08	-0.06		-0.37	-0.36
		(0.75)	(0.75)		(0.92)	(0.92)
Service-sector workers		0.40	0.40		0.09	0.09
		(0.89)	(0.89)		(1.04)	(1.04)
Owner-managers		0.35	0.35		0.03	0.02
		(1.07)	(1.07)		(1.23)	(1.23)
Executives		0.04	0.04		-0.46	-0.45
		(1.05)	(1.05)		(1.19)	(1.19)
Others		0.79	0.80		0.44	0.48
		(0.85)	(0.85)		(1.04)	(1.04)
Dependents (baseline: No dependent)						
One dependent		-0.52	-0.51		-0.69	-0.68
		(1.05)	(1.05)		(1.16)	(1.16)
Two dependents		-0.67	-0.66		-1.32	-1.29
		(0.79)	(0.79)		(0.85)	(0.85)
More than two dependents		-1.49	-1.50		-0.33	-0.37
		(1.13)	(1.13)		(0.42)	(0.41)
Constant	1.56***	12.31***	12.62***			
	(0.00)	(4.67)	(4.70)			
Observations	296,092	296,092	296,092	273,616	273,616	273,616

First-stage F-stat.	/	/	/	403.0	394.0	378.8
R^2-Adjusted	0.402	0.402	0.402	/	/	/
Uncond. Mean(Dona. Amt_{t+1})	\$1.42	\$1.42	\$1.42	\$1.42	\$1.42	\$1.42
Cond. Mean(Dona. Amt_{t+1})	\$97.10	\$97.10	\$97.10	\$97.10	\$97.10	\$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES

Panel C: First stage regression of instrumental variable approach

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Income uncertainty			
Firm-level average of income				0.60***	0.57***	0.56***
uncertainty (leave-one-out)				(0.03)	(0.03)	(0.03)
Income					-0.07***	-0.07***
					(0.00)	(0.00)
Financial wealth					0.01***	0.01***
					(0.00)	(0.00)
Age × Age					-0.00***	-0.00***
					(0.00)	(0.00)
Married					0.03*	0.04*
					(0.02)	(0.02)
Education (baseline: Graduate school and above)						
Undergraduate					-0.07*	-0.08**
					(0.04)	(0.04)
Vocational school					-0.15***	-0.15***
					(0.04)	(0.04)
High school and below					-0.14***	-0.14***
					(0.04)	(0.04)
Occupation (baseline: Public sector officers)						
Agricultural workers					-0.06	-0.11
					(0.32)	(0.32)
Blue-collar workers					0.17**	0.18***
					(0.07)	(0.07)
White-collar workers					0.19***	0.20***
					(0.07)	(0.07)
Service-sector workers					0.12*	0.13*
					(0.07)	(0.07)
Owner-managers					0.16*	0.18**
					(0.09)	(0.09)
Executives					0.23***	0.24***
					(0.07)	(0.07)
Others					0.28***	0.27***
					(0.07)	(0.07)
Dependents (baseline: No dependent)						
One dependent					0.06	0.06
					(0.05)	(0.05)
Two dependents					0.16***	0.15***
					(0.06)	(0.06)
More than two dependents					-0.03	-0.03
					(0.17)	(0.17)
Observations				273,616	273,616	273,616
F test statistics				403.0	394.0	378.8
Control variables				NO	YES	YES

Individual fixed effect	YES	YES	YES
Quarter fixed effect	YES	YES	YES
City × quarter fixed effect	NO	NO	YES

Notes: This table reports the full set of coefficients of regressions predicting donation behavior using individual-level income uncertainty. The dependent variable is the next-quarter likelihood to donate in Panel A and the next-quarter donation amount in Panel B. The main independent variable of interest, income uncertainty, is the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters. Control variables include the current quarter's income (in logarithms), financial wealth (in logarithms), and demographic variables that include age (omitted due to multi-collinearity), age squared, educational attainment, occupational type, marital status, and the number of dependents. All currency units are converted to USD at the exchange rate. Columns (1)-(3) of Panels A and B report OLS estimates, while columns (4)-(6) report instrumental variable estimates, where individual-level income uncertainty is instrumented by the firm-level leave-one-out average of income uncertainty. Panel C validates the instrumental variable approach by presenting the first-stage regression results, showing the relationship between the instrument (firm-level leave-one-out average of income uncertainty) and the endogenous variable (individual-level income uncertainty), alongside other control variables. Standardized coefficients are reported for all continuous independent variables, including income uncertainty. Standard errors are clustered at the individual level and are reported beneath the estimated coefficient within parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Predicting Donations using Income Uncertainty (Alternative model specifications)

Panel A: Income uncertainty computed using realized monthly payroll income in three recent quarters (instead of four)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable		Pr(donation$_{t+1}$)			Donation amount$_{t+1}$	
Income uncertainty$_t$	0.42%***	0.43%***	0.44%***	0.38***	0.38***	0.39***
	(0.04%)	(0.04%)	(0.04%)	(0.05)	(0.05)	(0.05)
Income$_t$		0.00	0.00		0.02	0.03
		(0.02)	(0.02)		(0.02)	(0.02)
Observations	370,115	370,115	370,115	370,115	370,115	370,115
R^2-Adjusted	0.245	0.245	0.246	0.212	0.212	0.212
Dep. var. mean	1.46%	1.46%	1.46%	1.42	1.42	1.42
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES
Panel B: Income uncertainty computed using realized monthly payroll income in two recent quarters (instead of four)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable		Pr(donation t+1)			Donation amount t+1	
Income uncertainty$_t$	0.26%***	0.24%***	0.24%***	0.22***	0.21***	0.21***
	(0.03%)	(0.03%)	(0.03%)	(0.04)	(0.04)	(0.04)
Income$_t$		0.01	0.02		0.03	0.03
		(0.02)	(0.02)		(0.02)	(0.02)
Observations	444,138	444,138	444,138	444,138	444,138	444,138
R^2-Adjusted	0.217	0.217	0.218	0.212	0.212	0.212
Dep. var. mean	1.46%	1.46%	1.46%	1.42	1.42	1.42
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES
Panel C: Predicting donations in the next month (instead of donations in the next quarter)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable		Pr(donation t+1)			Donation amount t+1	
Income uncertainty$_t$	0.26%***	0.26%***	0.27%***	0.18***	0.19***	0.20***
	(0.02%)	(0.02%)	(0.02%)	(0.02)	(0.02)	(0.02)
Income$_t$		0.01	-0.00		0.02	0.02
		(0.02)	(0.02)		(0.02)	(0.02)
Observations	888,276	888,276	888,276	888,276	888,276	888,276
R^2-Adjusted	0.602	0.602	0.602	0.181	0.181	0.181
Dep. var. mean	1.01%	1.01%	1.01%	0.52	0.52	0.52
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Month fixed effect	YES	YES	YES	YES	YES	YES
City × month fixed effect	NO	NO	YES	NO	NO	YES

Notes: This table reports estimates of regressions predicting donation behavior using alternative model specifications. Panels A and B report the specifications where income uncertainty is computed using realized monthly payroll income in a shorter 3-quarter or 2-quarter recent period (instead of the baseline four quarters) as the independent variable, respectively. Panel C reports the specification where we alternatively predict donations in the next month (instead of the baseline donations in the next quarter) using the income uncertainty independent variable as computed in the baseline. The dependent variables in columns (1)-(3) and columns (4)-(6) are the likelihood to donate, and the donation amount, respectively. Control variables include the income for the same period as donation (in logarithms), financial wealth (in logarithms), and demographic variables that include age, age squared, educational attainment, occupational type, marital status, and the number of dependents. All currency units are converted to USD at the exchange rate. Standardized coefficients are reported for all continuous independent variables, including income uncertainty. Standard errors are clustered at the individual level and are reported beneath the estimated coefficient within parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.4: Income Uncertainty Predicts Donation: Religious Donation and Negative Uncertainty (Full set of control coefficients)

Panel A: Probability of donation $(t+1)$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable					Pr(donation$_{t+1}$)			
Foundation type	Religious	Secular	Religious	Secular	Religious	Secular	Religious	Secular
Specification	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Income	0.47%***	0.24%***			1.23%***	0.64%		
uncertainty$_t$	(0.04%)	(0.04%)			(0.45%)	(0.40%)		
Positive			0.19%***	0.09%***			0.36%	0.17%
uncertainty$_t$			(0.03%)	(0.02%)			(0.23%)	(0.20%)
Negative			0.27%***	0.15%***			1.06%*	0.39%
uncertainty$_t$			(0.05%)	(0.04%)			(0.55%)	(0.47%)
Income$_t$	0.05*	-0.06***	0.04*	-0.06***	0.10**	-0.03	0.10**	-0.04
	(0.03)	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Financial wealth$_t$	0.00	0.02	0.00	0.02	0.00	0.01	0.01	0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Age squared	-0.00	-0.00***	-0.00	-0.00***	0.00	-0.00**	0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	0.27	-0.20	0.27	-0.20	0.25	-0.07	0.24	-0.08
	(0.25)	(0.25)	(0.25)	(0.25)	(0.28)	(0.26)	(0.28)	(0.26)
Education (baseline: Graduate school and above)								
Undergraduate	-0.28	-0.42	-0.28	-0.42	-0.42	-0.19	-0.41	-0.20
	(0.53)	(0.47)	(0.53)	(0.47)	(0.56)	(0.46)	(0.56)	(0.46)
Vocational school	0.39	-0.74	0.39	-0.74	0.28	-0.46	0.30	-0.47
	(0.58)	(0.56)	(0.58)	(0.56)	(0.61)	(0.55)	(0.61)	(0.55)
High school and below	-0.17	-0.57	-0.17	-0.57	-0.24	-0.21	-0.22	-0.23
	(0.53)	(0.57)	(0.53)	(0.57)	(0.54)	(0.53)	(0.55)	(0.53)
Occupation (baseline: Public sector officers)								
Agricultural workers	0.73	-0.15	0.71	-0.15	1.01	0.07	1.03	0.05
	(1.01)	(0.59)	(1.01)	(0.59)	(1.22)	(0.70)	(1.21)	(0.68)
Blue-collar workers	0.53	-0.35	0.53	-0.35	0.43	-0.52	0.46	-0.49
	(0.90)	(0.51)	(0.90)	(0.51)	(1.07)	(0.61)	(1.08)	(0.61)
White-collar workers	0.44	-0.50	0.44	-0.50	0.35	-0.68	0.37	-0.66
	(0.91)	(0.51)	(0.92)	(0.51)	(1.09)	(0.61)	(1.09)	(0.61)
Service-sector workers	0.95	-1.06*	0.94	-1.06*	0.84	-1.28**	0.85	-1.26*
	(1.03)	(0.56)	(1.03)	(0.56)	(1.20)	(0.65)	(1.20)	(0.65)
Owner-managers	0.97	-0.43	0.96	-0.44	0.95	-0.63	0.89	-0.63
	(0.95)	(0.99)	(0.95)	(0.99)	(1.12)	(1.10)	(1.12)	(1.10)
Executives	1.45	-0.53	1.44	-0.53	1.48	-0.73	1.47	-0.70
	(0.98)	(0.63)	(0.98)	(0.63)	(1.14)	(0.73)	(1.14)	(0.73)
Others	1.07	-0.49	1.06	-0.49	1.03	-0.68	1.02	-0.66
	(0.93)	(0.51)	(0.93)	(0.51)	(1.10)	(0.61)	(1.10)	(0.61)
Dependents (baseline: No dependent)								
One dependent	-1.38*	0.28	-1.38*	0.28	-1.56**	0.24	-1.53*	0.26
	(0.71)	(0.50)	(0.71)	(0.49)	(0.78)	(0.54)	(0.78)	(0.54)
Two dependents	-0.54	-0.38	-0.54	-0.38	-0.74	-0.99*	-0.75	-0.97*
	(0.84)	(0.58)	(0.84)	(0.58)	(0.93)	(0.54)	(0.92)	(0.54)
More than two dependents	-0.64	-1.18	-0.64	-1.18	-0.67	-0.08	-0.66	-0.07
	(0.59)	(1.11)	(0.59)	(1.11)	(0.66)	(0.16)	(0.66)	(0.15)
Constant	0.63	9.12***	0.67	9.11***				

	(3.10)	(2.54)	(3.10)	(2.54)				
Observations	296,092	296,092	296,092	296,092	273,616	273,616	273,616	273,616
First-stage F-stat.	/	/	/	/	378.8	378.8	159.7	159.7
R^2-Adjusted	0.382	0.383	0.382	0.383	/	/	/	/
Mean Pr(Donation$_{t+1}$)	0.89%	0.61%	0.89%	0.61%	0.89%	0.61%	0.89%	0.61%
Cond. Mean(Dona. Amt$_{t+1}$)	$94.4	$94.4	$94.4	$94.4	$94.4	$94.4	$94.4	$94.4
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Donation amount ($t+1$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable				Donation amount$_{t+1}$				
Foundation type	Religious	Secular	Religious	Secular	Religious	Secular	Religious	Secular
Specification	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Income	0.32***	0.21***			1.40**	0.73*		
uncertainty$_t$	(0.04)	(0.04)			(0.71)	(0.43)		
Positive			0.13***	0.07***			0.36	0.23
uncertainty$_t$			(0.02)	(0.03)			(0.33)	(0.21)
Negative			0.19***	0.14***			1.27*	0.35
uncertainty$_t$			(0.05)	(0.04)			(0.77)	(0.50)
Income$_t$	0.03	-0.05	0.03	-0.05	0.12**	-0.00	0.12*	-0.01
	(0.05)	(0.04)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)
Financial wealth$_t$	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Age squared	-0.00	-0.01***	-0.00	-0.01***	-0.00	-0.00**	-0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	0.26	-0.10	0.26	-0.11	0.25	0.01	0.23	0.01
	(0.20)	(0.21)	(0.20)	(0.21)	(0.22)	(0.21)	(0.22)	(0.21)
Education (baseline: Graduate school and above)								
Undergraduate	-0.14	-0.57	-0.14	-0.57	-0.14	-0.34	-0.13	-0.35
	(0.38)	(0.41)	(0.38)	(0.41)	(0.42)	(0.39)	(0.43)	(0.39)
Vocational school	0.37	-0.66	0.37	-0.66	0.42	-0.36	0.45	-0.38
	(0.42)	(0.48)	(0.42)	(0.48)	(0.46)	(0.45)	(0.47)	(0.45)
High school and below	-0.14	-0.69	-0.14	-0.69	-0.05	-0.34	-0.03	-0.36
	(0.36)	(0.51)	(0.36)	(0.51)	(0.40)	(0.45)	(0.41)	(0.45)
Occupation (baseline: Public sector officers)								
Agricultural workers	0.83	-0.20	0.81	-0.21	1.07	0.03	1.11	-0.01
	(0.62)	(0.59)	(0.62)	(0.59)	(0.83)	(0.68)	(0.79)	(0.66)
Blue-collar workers	0.60	-0.45	0.59	-0.45	0.48	-0.65	0.53	-0.63
	(0.53)	(0.51)	(0.53)	(0.51)	(0.65)	(0.61)	(0.65)	(0.61)
White-collar workers	0.47	-0.53	0.46	-0.53	0.36	-0.74	0.39	-0.71
	(0.53)	(0.51)	(0.53)	(0.52)	(0.65)	(0.62)	(0.66)	(0.62)
Service-sector workers	1.13	-0.73	1.12	-0.73	1.02	-0.95	1.06	-0.94
	(0.72)	(0.51)	(0.72)	(0.51)	(0.83)	(0.60)	(0.83)	(0.60)
Owner-managers	0.94	-0.59	0.94	-0.59	0.80	-0.81	0.73	-0.79
	(0.61)	(0.86)	(0.61)	(0.86)	(0.72)	(0.97)	(0.74)	(0.97)
Executives	1.09*	-1.05	1.09*	-1.05	0.84	-1.32	0.83	-1.29
	(0.63)	(0.75)	(0.63)	(0.75)	(0.72)	(0.84)	(0.72)	(0.84)
Others	1.06*	-0.25	1.05*	-0.25	0.91	-0.46	0.91	-0.43
	(0.57)	(0.57)	(0.57)	(0.57)	(0.70)	(0.69)	(0.71)	(0.69)
Dependents (baseline: No dependent)								
One dependent	-1.06	0.55	-1.06	0.55	-1.23	0.55	-1.18	0.56
	(0.95)	(0.45)	(0.95)	(0.45)	(1.05)	(0.50)	(1.05)	(0.50)
Two dependents	-0.62	-0.03	-0.62	-0.03	-0.87	-0.44*	-0.88	-0.41*

	(0.73)	(0.30)	(0.73)	(0.30)	(0.81)	(0.24)	(0.81)	(0.24)
More than two dependents	-0.32	-1.18	-0.31	-1.18	-0.31	-0.06	-0.29	-0.06
	(0.24)	(1.10)	(0.24)	(1.10)	(0.32)	(0.16)	(0.31)	(0.13)
Constant	3.20	9.54***	3.22	9.53***				
	(3.86)	(2.51)	(3.86)	(2.50)				
Observations	296,092	296,092	296,092	296,092	273,616	273,616	273,616	273,616
First-stage F-stat.	/	/	/	/	378.8	378.8	159.7	159.7
R^2-Adjusted	0.368	0.444	0.368	0.444	/	/	/	/
Uncond. Mean(Dona. Amt$_{t+1}$)	$0.84	$0.58	$0.84	$0.58	$0.84	$0.58	$0.84	$0.58
Cond. Mean(Dona. Amt$_{t+1}$)	$94.4	$94.4	$94.4	$94.4	$94.4	$94.4	$94.4	$94.4
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the full set of coefficients of regressions where within-person variations in income uncertainty predict the likelihood and amount of donations to religious foundations and donations to secular foundations. The dependent variable is the next-quarter likelihood to donate in Panel A and the next-quarter donation amount in Panel B for the respective foundation type. The main independent variables of interest include income uncertainty, as the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters, and positive income uncertainty and negative income uncertainty, as constructed using the semi-variance approach. Columns (1)-(4) report OLS estimates. Columns (5)-(8) report instrumental variable estimates, where individual-level (positive, negative) income uncertainty is instrumented by the firm-level leave-one-out average of (positive, negative) income uncertainty. Control variables are log income, log financial wealth, and demographic variables that include age, age squared, education, occupation, marital status, and number of dependents. Standardized coefficients are reported for all continuous independent variables, including income uncertainty. All currency units are converted to USD. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.5: Religious and Secular Donations: Adjusting for Multiple Hypothesis Testing

		p-values for one-sided tests of the null hypothesis (H0)	
Religious v.s. secular hypotheses (null hypothesis is no difference)	Coeff. difference	Unadjusted	Romano-Wolf adjusted
Predictive effect of income uncertainty on religious versus secular donation probability (Table 3, higher is stronger effect)	0.23%	0.000***	0.004***
Predictive effect of income uncertainty on religious versus secular donation amount (Table 3, higher is stronger effect)	0.11	0.026**	0.049**
Predictive effect of health shocks on religious versus secular donation probability (Table 4, higher is stronger effect)	2.30%	0.000***	0.002***
Predictive effect of health shocks on religious versus secular donation amount (Table 4, higher is stronger effect)	1.87	0.000***	0.002***
Association with insurance expenditure for incidence of religious versus secular donation (Table 5, lower is more substitutable)	-45.13	0.186	0.213
Association with insurance expenditure for amount of religious versus secular donation (Table 5, lower is more substitutable)	-3.74	0.186	0.249

Notes: This table reports the unadjusted p-values for the difference between the coefficients on religious and secular contributions in Tables 3, 4, and 5 and the p-values after adjusting for multiple hypothesis testing using the Romano-Wolf method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.6: Positive vs. Negative Shocks: Adjusting for Multiple Hypothesis Testing

Positive v.s. negative hypotheses (null hypothesis is no difference)	Coeff. difference	p-values for one-sided tests of the null hypothesis (H0): Unadjusted	Romano-Wolf adjusted
Predictive effect of positive vs. negative income uncertainty on religious donation probability (Table 3, higher is stronger effect)	-0.085%	0.081*	0.121
Predictive effect of positive vs. negative income uncertainty on religious donation amount (Table 3, higher is stronger effect)	-0.063	0.118	0.162
Predictive effect of positive vs. negative income uncertainty on secular donation probability (Table 3, higher is stronger effect)	-0.066%	0.140	0.221
Predictive effect of positive vs. negative income uncertainty on secular donation amount (Table 3, higher is stronger effect)	-0.063	0.124	0.191
Predictive effect of positive vs. negative income uncertainty on insurance purchase (Table A.9, higher is stronger effect)	-33.42	0.000***	0.001***
Sensitivity change with the donation dummy in the income uncertainty (positive vs. negative) and insurance expenditure relationship (Table A.9, lower is stronger effect)	49.46	0.037**	0.058*
Sensitivity change with the donation amount in the income uncertainty (positive vs. negative) and insurance expenditure relationship (Table A.9, lower is stronger effect)	4.46	0.063*	0.092*

Notes: This table reports the unadjusted p-values for the difference between the coefficients on positive and negative uncertainty in Tables 3 and A.9 and the p-values after adjusting for multiple hypothesis testing using the Romano-Wolf method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.7: Health Shocks Predict Donation: Religious Donation and Secular Donation (Full Set of Control Coefficients)

Panel A: Probability of donation $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			$\Pr(\text{donation}_{t+1})$			
Foundation type	All	Religious	Secular	All	Religious	Secular
Health shock occurrence$_t$	3.94%***	3.15%***	0.85%***			
	(0.25%)	(0.21%)	(0.14%)			
Health shock amount$_t$				0.76%***	0.61%***	0.16%***
				(0.21%)	(0.17%)	(0.05%)
Income$_t$	-0.01	0.06	-0.08**	-0.02	0.05	-0.08**
	(0.06)	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)
Financial wealth$_t$	0.03	0.01	0.02	0.02	0.01	0.02
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Age squared	-0.01**	-0.00	-0.01***	-0.01**	-0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	0.03	0.26	-0.20	0.06	0.28	-0.19
	(0.35)	(0.25)	(0.25)	(0.35)	(0.25)	(0.25)
Education (baseline: Graduate school and above)						
Undergraduate	-0.71	-0.32	-0.44	-0.70	-0.30	-0.44
	(0.69)	(0.52)	(0.47)	(0.70)	(0.53)	(0.47)
Vocational school	-0.52	0.38	-0.76	-0.55	0.35	-0.77
	(0.78)	(0.57)	(0.56)	(0.79)	(0.57)	(0.56)
High school and below	-0.78	-0.16	-0.58	-0.82	-0.20	-0.59
	(0.76)	(0.52)	(0.57)	(0.77)	(0.53)	(0.57)
Occupation (baseline: Public sector officers)						
Agricultural workers	-0.66	-0.22	-0.42	0.37	0.61	-0.20
	(1.29)	(1.11)	(0.58)	(1.20)	(1.01)	(0.58)
Blue-collar workers	0.27	0.62	-0.31	0.28	0.63	-0.30
	(1.04)	(0.90)	(0.51)	(1.04)	(0.90)	(0.51)
White-collar workers	0.20	0.62	-0.43	0.13	0.56	-0.44
	(1.05)	(0.91)	(0.51)	(1.05)	(0.91)	(0.51)
Service-sector workers	0.15	1.14	-0.99*	-0.03	1.00	-1.03*
	(1.17)	(1.03)	(0.56)	(1.18)	(1.03)	(0.56)
Owner-managers	0.73	1.06	-0.39	0.71	1.04	-0.40
	(1.37)	(0.95)	(0.98)	(1.37)	(0.95)	(0.98)
Executives	1.25	1.57	-0.47	1.22	1.55	-0.48
	(1.16)	(0.97)	(0.63)	(1.16)	(0.97)	(0.63)
Others	0.81	1.28	-0.40	0.72	1.21	-0.42
	(1.06)	(0.93)	(0.51)	(1.06)	(0.93)	(0.51)
Dependents (baseline: No dependent)						
One dependent	-0.95	-1.27*	0.32	-1.05	-1.35*	0.30
	(0.86)	(0.70)	(0.50)	(0.87)	(0.71)	(0.50)
Two dependents	-0.85	-0.51	-0.35	-0.84	-0.49	-0.35
	(1.01)	(0.84)	(0.57)	(1.02)	(0.84)	(0.58)
More than two dependents	-1.78	-0.62	-1.18	-1.79	-0.63	-1.18
	(1.24)	(0.57)	(1.11)	(1.25)	(0.59)	(1.11)
Constant	10.31***	0.95	9.42***	10.93***	1.44	9.55***
	(3.94)	(3.09)	(2.54)	(3.95)	(3.10)	(2.54)
Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.387	0.386	0.383	0.385	0.384	0.383

Mean Pr(Donation$_{t+1}$)	1.46%	0.89%	0.61%	1.46%	0.89%	0.61%
Cond. Mean(Dona. Amt$_{t+1}$)	\$97.10	\$94.39	\$94.40	\$97.10	\$94.39	\$94.40
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES

Panel B: Donation amount ($t+1$)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Donation amount$_{t+1}$			
Foundation type	All	Religious	Secular	All	Religious	Secular
Health shock occurrence$_t$	2.08***	1.98***	0.11			
	(0.23)	(0.20)	(0.12)			
Health shock amount$_t$				0.44***	0.42***	0.02
				(0.13)	(0.12)	(0.02)
Income$_t$	-0.05	0.01	-0.06	-0.05	0.01	-0.06
	(0.06)	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)
Financial wealth$_t$	0.04**	0.03	0.02	0.04**	0.03	0.02
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Age squared	-0.01**	-0.00	-0.01***	-0.01**	-0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	0.16	0.25	-0.10	0.17	0.27	-0.10
	(0.29)	(0.20)	(0.21)	(0.29)	(0.20)	(0.21)
Education (baseline: Graduate school and above)						
Undergraduate	-0.74	-0.16	-0.58	-0.73	-0.15	-0.58
	(0.56)	(0.38)	(0.41)	(0.56)	(0.38)	(0.41)
Vocational school	-0.33	0.36	-0.69	-0.35	0.34	-0.69
	(0.64)	(0.41)	(0.48)	(0.65)	(0.42)	(0.48)
High school and below	-0.85	-0.14	-0.71	-0.87	-0.16	-0.71
	(0.62)	(0.35)	(0.51)	(0.62)	(0.36)	(0.51)
Occupation (baseline: Public sector officers)						
Agricultural workers	-0.04	0.23	-0.27	0.51	0.74	-0.24
	(0.91)	(0.66)	(0.59)	(0.91)	(0.62)	(0.59)
Blue-collar workers	0.24	0.66	-0.42	0.24	0.66	-0.42
	(0.74)	(0.53)	(0.51)	(0.74)	(0.53)	(0.51)
White-collar workers	0.09	0.58	-0.49	0.06	0.55	-0.49
	(0.75)	(0.53)	(0.51)	(0.75)	(0.53)	(0.51)
Service-sector workers	0.55	1.25*	-0.70	0.45	1.16	-0.71
	(0.89)	(0.72)	(0.51)	(0.89)	(0.72)	(0.51)
Owner-managers	0.45	1.00	-0.55	0.43	0.99	-0.56
	(1.07)	(0.61)	(0.86)	(1.07)	(0.61)	(0.86)
Executives	0.17	1.17*	-1.00	0.16	1.16*	-1.00
	(1.05)	(0.63)	(0.75)	(1.05)	(0.63)	(0.75)
Others	1.00	1.20**	-0.19	0.95	1.15**	-0.20
	(0.85)	(0.57)	(0.57)	(0.85)	(0.57)	(0.57)
Dependents (baseline: No dependent)						
One dependent	-0.42	-0.99	0.57	-0.48	-1.04	0.56
	(1.05)	(0.95)	(0.45)	(1.05)	(0.95)	(0.45)
Two dependents	-0.60	-0.59	-0.01	-0.59	-0.59	-0.01
	(0.79)	(0.73)	(0.30)	(0.79)	(0.73)	(0.30)
More than two dependents	-1.49	-0.30	-1.18	-1.49	-0.31	-1.18
	(1.12)	(0.23)	(1.10)	(1.13)	(0.24)	(1.10)
Constant	13.32***	3.44	9.87***	13.64***	3.75	9.89***
	(4.66)	(3.87)	(2.51)	(4.66)	(3.86)	(2.51)
Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.402	0.369	0.443	0.402	0.369	0.443

Uncond. Mean(Dona. Amt$_{t+1}$)	\$1.42	\$0.84	\$0.58	\$1.42	\$0.84	\$0.58
Cond. Mean(Dona. Amt$_{t+1}$)	\$97.10	\$94.39	\$94.40	\$97.10	\$94.39	\$94.40
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES

Notes: This table reports the full set of coefficients of regressions where within-person variations in health shocks predict the likelihood and amount of donations to all foundations, to religious foundations, and to secular foundations. The dependent variable is the quarter $t+1$ likelihood to donate in Panel A and the donation amount in Panel B for the respective foundation type. The main dependent variable of interest, health shock, is defined as the dummy of incurring medical expenditures in the past quarter that are above the median of the sample in Columns (1)-(3), and as the amount spent on medical expenditures in the past quarter that are above the median of the sample in Columns (4)-(6). Control variables and fixed effects are the same as in Table A.2. All currency units are converted to USD at the exchange rate. Standardized coefficients are reported for all continuous independent variables. Standard errors are clustered at the individual level and are reported beneath the estimated coefficient within parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.8: Donation Associated with Reduction in Insurance Expenditures (Full set of control coefficients)

Panel A: Whether donated in the same quarter ($t+1$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Insurance expenditures$_{t+1}$ (\$)			
Foundation type	All	Religious	Secular	All	Religious	Secular
Donation dummy$_{t+1}$	-71.03***	-89.95***	-44.82	15.54	18.16	13.52
	(23.00)	(28.84)	(34.84)	(35.39)	(46.16)	(52.60)
Income uncertainty$_t$ × Donation dummy$_{t+1}$				-96.68***	-119.33**	-64.78
				(36.29)	(50.04)	(47.91)
Income uncertainty$_t$	100.04***	99.97***	99.65***	101.53***	101.10***	100.05***
	(5.83)	(5.83)	(5.83)	(5.87)	(5.86)	(5.83)
Income$_t$	31.68***	31.73***	31.66***	31.56***	31.65***	31.63***
	(3.68)	(3.69)	(3.69)	(3.69)	(3.69)	(3.69)
Financial wealth$_t$	0.25	0.24	0.24	0.20	0.19	0.23
	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)
Age squared	0.78**	0.78**	0.78**	0.78**	0.78**	0.78**
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Married	5.58	5.80	5.47	5.41	5.32	5.60
	(46.87)	(46.87)	(46.87)	(46.87)	(46.87)	(46.87)
Education (baseline: Graduate school and above)						
Undergraduate	-143.77	-143.56	-143.49	-143.94	-143.82	-143.45
	(127.16)	(127.17)	(127.15)	(127.19)	(127.20)	(127.15)
Vocational school	-111.86	-111.16	-111.85	-112.03	-111.24	-111.99
	(157.31)	(157.31)	(157.30)	(157.33)	(157.33)	(157.30)
High school and below	-249.94*	-249.55*	-249.65*	-250.34*	-250.00*	-249.69*
	(145.04)	(145.05)	(145.04)	(145.06)	(145.06)	(145.04)
Occupation (baseline: Public sector officers)						
Agricultural workers	-25.68	-25.45	-26.12	-24.48	-24.26	-25.89
	(231.63)	(231.62)	(231.65)	(231.57)	(231.53)	(231.66)
Blue-collar workers	-83.97	-83.60	-84.23	-83.52	-83.06	-84.21
	(226.17)	(226.16)	(226.23)	(226.14)	(226.11)	(226.23)
White-collar workers	-49.17	-48.75	-49.37	-48.50	-48.11	-49.31
	(231.19)	(231.18)	(231.24)	(231.15)	(231.12)	(231.25)
Service-sector workers	-135.08	-134.15	-135.48	-133.84	-132.63	-135.50
	(239.00)	(238.98)	(239.06)	(238.97)	(238.94)	(239.06)
Owner-managers	-132.45	-132.02	-133.08	-131.59	-130.56	-133.43
	(271.95)	(271.94)	(272.00)	(271.91)	(271.90)	(272.00)
Executives	-35.52	-34.98	-36.52	-34.56	-33.87	-36.76
	(240.06)	(240.05)	(240.12)	(240.03)	(240.00)	(240.13)
Others	-5.74	-5.15	-6.32	-5.48	-4.67	-6.24
	(230.20)	(230.19)	(230.25)	(230.16)	(230.14)	(230.26)
Dependents (baseline: No dependent)						
One dependent	-52.60	-53.07	-51.70	-51.67	-51.09	-52.15
	(108.10)	(108.10)	(108.11)	(108.11)	(108.12)	(108.11)
Two dependents	109.22	109.38	109.70	111.87	112.33	109.87
	(76.59)	(76.62)	(76.59)	(76.57)	(76.58)	(76.60)
More than two dependents	202.91	203.62	203.67	203.88	204.46	203.85
	(209.56)	(209.56)	(209.55)	(209.55)	(209.55)	(209.55)
Constant	-1,438.19***	-1,445.40***	-1,440.93***	-1,437.44***	-1,442.47***	-1,441.72***
	(548.09)	(548.12)	(548.08)	(548.07)	(548.10)	(548.12)
Observations	296,092	296,092	296,092	296,092	296,092	296,092

R^2-Adjusted	0.169	0.169	0.169	0.169	0.169	0.169
Mean(Insur. exp. t+1)	$216.42	$216.42	$216.42	$216.42	$216.42	$216.42
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES

Panel B: Donation amount in the same quarter ($t+1$)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Insurance expenditures$_{t+1}$ ($)			
Foundation type	All	Religious	Secular	All	Religious	Secular
Donation amount$_{t+1}$	-3.73*	-5.25**	-1.51	1.22	0.55	2.50
	(2.05)	(2.63)	(3.71)	(2.76)	(3.37)	(5.18)
Income uncertainty$_t$ ×				-5.30**	-6.38**	-4.13
Donation amount$_{t+1}$				(2.18)	(2.80)	(3.82)
Income uncertainty$_t$	99.74***	99.71***	99.57***	100.49***	100.24***	99.82***
	(5.83)	(5.83)	(5.83)	(5.84)	(5.84)	(5.83)
Income$_t$	31.69***	31.71***	31.68***	31.63***	31.68***	31.66***
	(3.69)	(3.69)	(3.69)	(3.69)	(3.69)	(3.69)
Financial wealth$_t$	0.25	0.24	0.23	0.22	0.23	0.23
	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)
Age squared	0.78**	0.78**	0.78**	0.78**	0.78**	0.78**
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Married	5.61	5.69	5.54	5.67	5.56	5.68
	(46.87)	(46.87)	(46.87)	(46.87)	(46.87)	(46.87)
Education (baseline: Graduate school and above)						
Undergraduate	-143.56	-143.37	-143.38	-143.62	-143.43	-143.39
	(127.15)	(127.16)	(127.15)	(127.16)	(127.17)	(127.15)
Vocational school	-111.62	-111.32	-111.62	-111.57	-111.16	-111.66
	(157.30)	(157.30)	(157.29)	(157.30)	(157.31)	(157.29)
High school and below	-249.70*	-249.47*	-249.50*	-249.79*	-249.45*	-249.57*
	(145.04)	(145.04)	(145.04)	(145.04)	(145.05)	(145.04)
Occupation (baseline: Public sector officers)						
Agricultural workers	-25.85	-25.66	-26.10	-25.37	-25.42	-25.88
	(231.65)	(231.64)	(231.64)	(231.63)	(231.61)	(231.65)
Blue-collar workers	-84.02	-83.76	-84.14	-84.14	-83.84	-84.18
	(226.21)	(226.21)	(226.23)	(226.20)	(226.20)	(226.23)
White-collar workers	-49.17	-48.90	-49.22	-49.14	-48.87	-49.21
	(231.23)	(231.22)	(231.25)	(231.22)	(231.21)	(231.25)
Service-sector workers	-134.86	-134.42	-135.12	-134.49	-133.98	-135.09
	(239.03)	(239.03)	(239.06)	(239.03)	(239.02)	(239.06)
Owner-managers	-132.76	-132.40	-132.98	-132.60	-131.57	-133.37
	(271.99)	(271.99)	(272.01)	(271.98)	(271.98)	(272.01)
Executives	-36.27	-35.71	-36.44	-36.68	-35.40	-36.94
	(240.10)	(240.10)	(240.12)	(240.10)	(240.09)	(240.13)
Others	-5.81	-5.55	-6.14	-5.45	-5.55	-5.85
	(230.24)	(230.24)	(230.25)	(230.23)	(230.22)	(230.26)
Dependents (baseline: No dependent)						
One dependent	-52.02	-52.38	-51.74	-50.89	-50.61	-52.03
	(108.10)	(108.10)	(108.11)	(108.11)	(108.13)	(108.11)
Two dependents	109.62	109.54	109.86	110.90	111.06	109.88
	(76.61)	(76.61)	(76.60)	(76.59)	(76.59)	(76.60)
More than two dependents	203.64	204.03	204.02	203.97	204.31	204.12
	(209.55)	(209.55)	(209.55)	(209.55)	(209.55)	(209.55)
Constant	-1,440.79***	-1,444.19***	-1,443.97***	-1,441.83***	-1,444.85***	-1,444.48***
	(548.10)	(548.13)	(548.08)	(548.11)	(548.12)	(548.11)

Observations	296,092	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.169	0.169	0.169	0.169	0.169	0.169
Mean(Insur. exp.$_{t+1}$)	$216.42	$216.42	$216.42	$216.42	$216.42	$216.42
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City $\times$ quarter FE	YES	YES	YES	YES	YES	YES

Notes: This table reports the full set of coefficients of regressions examining the association between donations and insurance expenditures using within-person variations in insurance spending, donations, and income uncertainty. The dependent variable is the insurance expenditures in quarter $t+1$. In columns (1)-(3) of panel A, the main independent variables of interest are a donation dummy for donating to the corresponding type of foundations in quarter $t+1$, and income uncertainty, as the standard deviation of the unpredicted component of all realized log monthly payroll income in the last four quarters up to quarter t. In columns (4)-(6) of panel A, the interaction of income uncertainty$_t$ and donation dummy$_{t+1}$ is further added. In Panel B, donation dummy$_{t+1}$ is replaced with donation amount$_{t+1}$, the raw amount donated to the corresponding type of foundations in quarter $t+1$ (not standardized). Control variables and fixed effects are the same as in Table 2. Continuous control variables, including income uncertainty, are standardized. All currency units are converted to USD. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.9: Substitution of Donations and Insurance under Upside and Downside Income Uncertainty

Panel A: Donation in the same quarter ($t+1$)		
	(1)	(2)
Dependent variable	Insurance expenditures$_{t+1}$	
Donation dummy$_{t+1}$	-70.07***	2.67
	(23.00)	(35.37)
Positive uncertainty$_t$	34.34***	34.45***
	(3.50)	(3.51)
Negative uncertainty$_t$	67.76***	69.31***
	(6.70)	(6.76)
Positive uncertainty$_t \times$		-21.34
Donation dummy$_{t+1}$		(20.79)
Negative uncertainty$_t \times$		-70.81***
Donation dummy$_{t+1}$		(25.45)
Observations	296,092	296,092
R^2-Adjusted	0.169	0.169
Mean(Insur. exp.$_{t+1}$)	216.42	216.42
Control variables	YES	YES
Individual fixed effect	YES	YES
City $\times$ quarter fixed effect	YES	YES
Panel B: Donation amount in the same quarter ($t+1$)		
	(1)	(2)
Dependent variable	Insurance expenditures$_{t+1}$	
Donation amount$_{t+1}$	-3.67*	0.73
	(2.05)	(2.81)
Positive uncertainty$_t$	34.22***	34.14***
	(3.50)	(3.50)
Negative uncertainty$_t$	67.59***	68.68***
	(6.70)	(6.73)
Positive uncertainty$_t \times$		-0.62
Donation amount$_{t+1}$		(1.84)
Negative uncertainty$_t \times$		-5.08***
Donation amount$_{t+1}$		(1.91)
Observations	296,092	296,092
R^2-Adjusted	0.169	0.169
Mean(Insur. exp.$_{t+1}$)	216.42	216.42
Control variables	YES	YES
Individual fixed effect	YES	YES
City $\times$ quarter fixed effect	YES	YES

Notes: This table examines how the substitution between donations and insurance varies with upside versus downside income uncertainty. The dependent variable is insurance expenditure in quarter $t+1$. Positive uncertainty$_t$ and Negative uncertainty$_t$ are semivariance-based measures for upside and downside risk, respectively, calculated over the four quarters up to quarter t. Panel A uses a donation dummy as the key independent variable, while Panel B uses the raw donation amount ($, not standardized). Column (1) shows the main effects, while column (2) adds the interaction terms between the uncertainty measures and donation variables. Control variables include the current quarter's income (in logarithms), financial wealth (in logarithms), and demographic variables that include age, age squared, educational attainment, occupational type, marital status, and the number of dependents. All continuous control variables, including income uncertainty, are standardized. Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.10: Donation Associated with Reduction in Insurance Expenditures (Restricting to individuals unlikely to be financially-constrained)

Panel A: Whether donated in the same quarter ($t+1$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Insurance expenditures$_{t+1}$ (\$)					
Foundation type	All	Religious	Secular	All	Religious	Secular
Donation dummy$_{t+1}$	-54.76**	-71.19**	-32.73	41.79	54.30	23.75
	(24.40)	(29.89)	(38.02)	(37.61)	(48.17)	(57.17)
Income uncertainty$_t$ × Donation dummy$_{t+1}$				-106.97***	-136.36***	-62.92
				(38.66)	(52.40)	(52.32)
Income uncertainty$_t$	100.32***	100.27***	100.01***	101.99***	101.61***	100.40***
	(5.86)	(5.86)	(5.86)	(5.89)	(5.89)	(5.86)
Observations	271,624	271,624	271,624	271,624	271,624	271,624
R^2-Adjusted	0.181	0.181	0.181	0.181	0.181	0.181
Mean(Insur. exp.$_{t+1}$)	\$213.77	\$213.77	\$213.77	\$213.77	\$213.77	\$213.77
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES
Panel B: Donation amount in the same quarter ($t+1$)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Insurance expenditures$_{t+1}$ (\$)					
Foundation type	All	Religious	Secular	All	Religious	Secular
Donation amount$_{t+1}$	-2.68*	-4.43**	-0.41	3.15	3.04	3.23
	(1.47)	(2.22)	(4.15)	(3.30)	(4.30)	(5.58)
Income uncertainty$_t$ × Donation amount$_{t+1}$				-5.87**	-7.34**	-3.82
				(2.35)	(3.01)	(4.10)
Income uncertainty$_t$	100.08***	100.08***	99.94***	100.93***	100.69***	100.18***
	(5.86)	(5.86)	(5.86)	(5.86)	(5.86)	(5.85)
Observations	271,624	271,624	271,624	271,624	271,624	271,624
R^2-Adjusted	0.181	0.181	0.181	0.181	0.181	0.181
Mean(Insur. exp.$_{t+1}$)	\$213.77	\$213.77	\$213.77	\$213.77	\$213.77	\$213.77
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
City × quarter FE	YES	YES	YES	YES	YES	YES

Notes: This table reports results examining the substitutability between donations and insurance purchases for the sample unlikely to be cash-constrained. We consider the individual as unlikely to be constrained if she has income to spare in every month, after the observed expenditure on consumption and the maximum of (1) the observed expenditure and (2) the sample conditional average expenditure on donations and on insurance purchase. Specifically, we subtract from an individual's income in each month the sum of (1) the observed consumption in the month, (2) the maximum monthly amount spent on insurance over the sample period for the individual or the sample conditional average insurance purchase amount (whichever is greater) and (3) the maximum monthly amount spent on donations over the sample period for the individual or the sample conditional average donation amount (whichever is greater). The dependent variable is the amount of insurance purchased in the current quarter. All other model setup is the same as in Table 5.

Table A.11: Consumption Not Associated with Reduction in Insurance Expenditures (Placebo test for Table 5.)

Panel A: Whether high-spent in the same quarter ($t+1$)					
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Insurance expenditures$_{t+1}$ ($)				
High-spending dummy$_{t+1}$	-2.11	-2.13	-18.34	-12.39	-30.88
	(6.39)	(6.91)	(12.25)	(15.56)	(56.28)
Income uncertainty$_t$ $\times$	8.19	12.55	9.12	15.28	-24.80
High-spending dummy$_{t+1}$	(7.33)	(8.05)	(12.78)	(18.29)	(51.10)
Income uncertainty$_t$	94.97***	95.80***	98.36***	98.53***	99.87***
	(6.79)	(6.07)	(5.87)	(5.84)	(5.82)
Observations	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.169	0.169	0.169	0.169	0.169
High spending over __ percentile	50th	75th	90th	95th	99th
Dep. var. mean	$216.42	$216.42	$216.42	$216.42	$216.42
Control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
City $\times$ quarter FE	YES	YES	YES	YES	YES
Panel B: High-spent amount in the same quarter ($t+1$)					
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Insurance expenditures$_{t+1}$ ($)				
High-spending amount$_{t+1}$	-0.004	-0.003	-0.003	-0.004	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Income uncertainty$_t$ $\times$	0.0007	0.0006	0.0002	0.0005	0.0008
High-spending amount$_{t+1}$	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income uncertainty$_t$	98.81***	98.98***	99.35***	99.23***	99.30***
	(6.00)	(5.93)	(5.87)	(5.84)	(5.82)
Observations	296,092	296,092	296,092	296,092	296,092
R^2-Adjusted	0.169	0.169	0.169	0.169	0.169
High spending over __ percentile	50th	75th	90th	95th	99th
Dep. var. mean	$216.42	$216.42	$216.42	$216.42	$216.42
Control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
City $\times$ quarter FE	YES	YES	YES	YES	YES

Notes: The table reports the estimates of robustness check regression, in which donation in Table 5 are replaced by high-spending consumption. The dependent variable is the total amount of insurance purchases for the current quarter. Income uncertainty is the standard deviation of all observations of log monthly payroll income in the previous four quarters, after residualizing from the income measure the part that can be accounted for by demographic background variables and time fixed effects. High-spending dummy variables in Columns (1) to (5) represent whether the individual experience consumption over the 50th, 75th, 90th, 95th, and 99th percentile in the same quarter as insurance purchases, respectively. All other model setup is the same as in Table 5.

Table A.12: Mutual Insurance: Does Donations Improve the Degree of Consumption Insurance?

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Consumption (Year 2 - Year 1)					
Donation type	If donated in Year 1			Donation Amount in Year 1		
	Any donation	*Religious donation*	*Secular donation*	*Any donation*	*Religious donation*	*Secular donation*
Income (Year 2 - Year 1) × Donation	0.01	0.02	0.01	0.00	0.00	0.00
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Income (Year 2 - Year 1)	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Donation	348.21*	193.83	453.62*	0.45	0.41	0.67
	(189.55)	(245.92)	(267.58)	(0.41)	(0.43)	(0.86)
Control variables	YES	YES	YES	YES	YES	YES
Observations	74,023	74,023	74,023	74,023	74,023	74,023
R^2-Adjusted	0.01	0.01	0.01	0.01	0.01	0.01

Notes: This table reports how donation behavior affects the consumption pass-through of income fluctuations, and is a replication of Dehejia, DeLeire, and Luttmer (2007). The dependent variable is the difference between the consumption in the second year and the consumption in the first year. The independent variables include the difference between the income in the second year and the income in the first year, donation behaviors of the first year and control variables. Donation behaviors in columns (1)-(3) are dummy variables indicating whether at least a donation, religious donation, or secular donation occurs in the first year, respectively. Donation behaviors in columns (4)-(6) are the amounts of donation, religious donation, and secular donation made in the first year. Control variables include demographic background variables and financial wealth (in logarithms) in the first year. Demographic variables are age, the square of age, educational attainment, occupational type, marital status, and the number of dependents at the current month. All currency units are converted to USD at the exchange rate. Standard errors are clustered at the individual level and are reported beneath the estimated coefficient within parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.13: Income Uncertainty Predicts Donation
(Further excluding conventional bonus-disbursing months when computing income uncertainty)

Panel A: Probability of donation $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Pr(donation$_{t+1}$)			
Specification	OLS	OLS	OLS	IV	IV	IV
Income uncertainty$_t$	0.51%***	0.52%***	0.51%***	2.33%***	2.43%***	2.43%***
	(0.05%)	(0.05%)	(0.05%)	(0.70%)	(0.74%)	(0.77%)
Income$_t$		0.02	-0.01		0.11*	0.11
		(0.06)	(0.06)		(0.07)	(0.07)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	507.0	461.0	425.6
R^2-Adjusted	0.383	0.383	0.383	/	/	/
Mean Pr(Donation$_{t+1}$)	1.46%	1.46%	1.46%	1.46%	1.46%	1.46%
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES
Panel B: Donation amount $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Donation amount$_{t+1}$			
Specification	OLS	OLS	OLS	IV	IV	IV
Income uncertainty$_t$	0.42***	0.42***	0.40***	2.62***	2.75***	2.72**
	(0.05)	(0.05)	(0.05)	(0.97)	(1.03)	(1.07)
Income$_t$		-0.03	-0.05		0.16*	0.16*
		(0.06)	(0.06)		(0.09)	(0.09)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	507.0	461.0	425.6
R^2-Adjusted	0.402	0.402	0.402	/	/	/
Mean(Dona. Amt$_{t+1}$)	$1.42	$1.42	$1.42	$1.42	$1.42	$1.42
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES

Notes: Here, we conduct an additional robustness check where we stringently exclude payroll observations from traditional bonus months (January, February, July) in our computation of income uncertainty, to recognize that bonuses, customarily paid in these few months, constitute a particular seasonal component of income. While we view as plausible that individuals may do good deeds to sway blessings in a favorable bonus outcome, this additional robustness check is to ensure that our results are not purely driven by the seasonality of bonuses. The dependent variables are the probability of making a donation in $t+1$ (Panel A) and the total donation amount in $t+1$ (Panel B). The independent variable income uncertainty is the standard deviation of residual log monthly payroll income in the past four quarters after removing these months where bonuses are traditionally disbursed (January, February, July). All other model setup is the same as in Table 2.

Table A.14: Income Uncertainty Predicts Donation
(Controlling for tax considerations)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Probability of donation $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Pr(donation$_{t+1}$)			
Specification	OLS	OLS	OLS	IV	IV	IV
Panel A.1: Marginal tax rates calculated by extrapolating monthly income						
Income uncertainty$_t$	0.71%***	0.70%***	0.70%***	1.88%***	1.91%***	1.90%***
	(0.06%)	(0.06%)	(0.06%)	(0.56%)	(0.59%)	(0.60%)
Income$_t$		-0.03	-0.03		0.05	0.05
		(0.04)	(0.04)		(0.06)	(0.06)
Price of giving	-0.25	-0.46	-0.34	-0.87	-0.53	-0.41
	(0.48)	(0.56)	(0.56)	(0.57)	(0.59)	(0.60)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	401.62	388.94	373.93
R2-Adjusted	0.384	0.384	0.384	/	/	/
Mean Pr(Donation$_{t+1}$)	1.46%	1.46%	1.46%	1.46%	1.46%	1.46%
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES
Panel A.2: Marginal tax rates calculated by using ex-post annual income						
Income uncertainty$_t$	0.70%***	0.69%***	0.69%***	1.86%***	1.92%***	1.90%***
	(0.06%)	(0.06%)	(0.06%)	(0.56%)	(0.59%)	(0.61%)
Income$_t$		-0.04	-0.04		0.07	0.07
		(0.04)	(0.04)		(0.06)	(0.06)
Price of giving	-1.33	-1.71	-1.77	-0.76	-0.05	-0.12
	(1.06)	(1.22)	(1.32)	(1.04)	(1.32)	(1.34)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	402.22	393.98	378.73
R2-Adjusted	0.384	0.384	0.384	/	/	/
Mean Pr(Donation$_{t+1}$)	1.46%	1.46%	1.46%	1.46%	1.46%	1.46%
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES
Panel B: Donation amount $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Donation amount$_{t+1}$			
Specification	OLS	OLS	OLS	IV	IV	IV
Panel B.1: Marginal tax rates calculated by extrapolating monthly income						
Income uncertainty$_t$	0.53***	0.52***	0.53***	2.11***	2.17***	2.13**

	(0.06)	(0.06)	(0.06)	(0.78)	(0.81)	(0.83)
Income$_t$		0.01	0.02		0.13*	0.13*
		(0.04)	(0.04)		(0.07)	(0.08)
Price of giving	0.13	0.28	0.43	-0.63	0.30	0.46
	(0.48)	(0.57)	(0.57)	(0.65)	(0.60)	(0.60)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	401.62	388.94	373.93
R2-Adjusted	0.402	0.402	0.402	/	/	/
Mean (Dona. Amt$_{t+1}$)	$1.42	$1.42	$1.42	$1.42	$1.42	$1.42
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES
Panel B.2: Marginal tax rates calculated by using ex-post annual income						
Income uncertainty$_t$	0.53***	0.52***	0.52***	2.09***	2.17***	2.13**
	(0.06)	(0.06)	(0.06)	(0.77)	(0.82)	(0.84)
Income$_t$		-0.02	-0.02		0.12	0.12
		(0.04)	(0.04)		(0.08)	(0.08)
Price of giving	-1.51	-1.73	-1.83	-0.97	0.30	0.16
	(1.15)	(1.24)	(1.25)	(1.17)	(1.46)	(1.49)
Observations	296,092	296,092	296,092	273,616	273,616	273,616
First-stage F-stat.	/	/	/	402.22	393.98	378.73
R2-Adjusted	0.402	0.402	0.402	/	/	/
Mean (Dona. Amt$_{t+1}$)	$1.42	$1.42	$1.42	$1.42	$1.42	$1.42
Cond. Mean(Dona. Amt$_{t+1}$)	$97.10	$97.10	$97.10	$97.10	$97.10	$97.10
Control variables	NO	YES	YES	NO	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Quarter fixed effect	YES	YES	YES	YES	YES	YES
City × quarter fixed effect	NO	NO	YES	NO	NO	YES

Notes: This table reports the predictive effect of income uncertainty on donations controlling for tax considerations, to address the potential that income uncertainty may be correlated with the price of giving. The donations in our dataset are eligible for tax exemption, making the price of giving effectively one minus the marginal tax rate. Panels A.1 and B.1 report the imputed marginal tax rates based on extrapolating based on monthly payroll income, multiplied by twelve, to estimate annual income, and Panels A.2 and B.2 report the imputed marginal tax rates based on utilizing ex-post annual income for those with a complete calendar year in our dataset. For others, we extrapolated annual income using all available monthly income data, applying aggregate seasonality adjustment factors. All other model setup is the same as in Table 2.

Table A.15: ”Self-fulfilling hypothesis”? Donation Does Not Predict Reduction in Uncertainty
(Full set of control coefficients)

	(1)	(2)	(3)
Dependent variable		Income uncertainty$_{year=2}$	
Foundation type	All	Religious	Secular
Panel A: Donation dummy and future income uncertainty			
Donation dummy$_{year=1}$	0.05	0.05	0.07
	(0.03)	(0.03)	(0.05)
Donation dummy $\times$ Income uncertainty$_{year=1}$	-0.02	-0.01	-0.05
	(0.02)	(0.03)	(0.03)
Income uncertainty$_{year=1}$	0.389***	0.388***	0.389***
	(0.004)	(0.004)	(0.004)
Income$_{year=1}$	0.33***	0.33***	0.33***
	(0.01)	(0.01)	(0.01)
Financial wealth$_{year=1}$	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Age$_{year=1}$	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Age$_{year=1}$ squared	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Female	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)
Married$_{year=1}$	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Education$_{year=1}$ (baseline: Graduate school and above)			
Undergraduate	-0.21***	-0.21***	-0.21***
	(0.01)	(0.01)	(0.01)
Vocational school	-0.22***	-0.22***	-0.22***
	(0.01)	(0.01)	(0.01)
High school and below	-0.26***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.01)
Occupation$_{year=1}$ (baseline: Public sector officers)			
Agricultural workers	-0.24***	-0.24***	-0.24***
	(0.08)	(0.08)	(0.08)
Blue-collar workers	0.05**	0.05**	0.05**
	(0.02)	(0.02)	(0.02)
White-collar workers	0.16***	0.16***	0.16***
	(0.02)	(0.02)	(0.02)
Service-sector workers	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)
Owner-managers	0.05	0.05	0.05
	(0.04)	(0.04)	(0.04)
Executives	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)

Others	-0.02	-0.02	-0.02
	(0.03)	(0.03)	(0.03)
Dependents$_{year=1}$ (baseline: No dependent)			
One dependent	0.03**	0.03**	0.03*
	(0.01)	(0.01)	(0.01)
Two dependents	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
More than two dependents	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)
Constant	-4.55***	-4.56***	-4.56***
	(0.14)	(0.14)	(0.14)
Observations	74,023	74,023	74,023
R^2-Adjusted	0.351	0.351	0.351
Control variables	YES	YES	YES

Panel B: Donation amount and future income uncertainty			
Donation amount$_{year=1}$	-0.00000	-0.00002	0.00003
	(0.00005)	(0.00005)	(0.00010)
Donation amount $\times$ Income uncertainty$_{year=1}$	0.00002	0.00007	-0.00005
	(0.00005)	(0.00007)	(0.00008)
Income uncertainty$_{year=1}$	0.388***	0.388***	0.389***
	(0.004)	(0.004)	(0.004)
Income$_{year=1}$	0.33***	0.33***	0.33***
	(0.01)	(0.01)	(0.01)
Financial wealth$_{year=1}$	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Age$_{year=1}$	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Age$_{year=1}$ squared	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Female	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)
Married$_{year=1}$	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Education$_{year=1}$ (baseline: Graduate school and above)			
Undergraduate	-0.21***	-0.21***	-0.21***
	(0.01)	(0.01)	(0.01)
Vocational school	-0.22***	-0.22***	-0.22***
	(0.01)	(0.01)	(0.01)
High school and below	-0.26***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.01)
Occupation$_{year=1}$ (baseline: Public sector officers)			
Agricultural workers	-0.24***	-0.24***	-0.24***
	(0.08)	(0.08)	(0.08)
Blue-collar workers	0.05**	0.05**	0.05**
	(0.02)	(0.02)	(0.02)
White-collar workers	0.16***	0.16***	0.16***
	(0.02)	(0.02)	(0.02)

Service-sector workers	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)
Owner-managers	0.05	0.05	0.05
	(0.04)	(0.04)	(0.04)
Executives	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)
Others	-0.02	-0.02	-0.02
	(0.03)	(0.03)	(0.03)
Dependents$_{year=1}$ (baseline: No dependent)			
One dependent	0.03*	0.03*	0.03*
	(0.01)	(0.01)	(0.01)
Two dependents	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
More than two dependents	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)
Constant	-4.57***	-4.57***	-4.57***
	(0.14)	(0.14)	(0.14)
Observations	74,023	74,023	74,023
R^2-Adjusted	0.351	0.351	0.351
Control variables	YES	YES	YES

Notes: This table reports the full set of coefficients of regressions examining the association between donation and future income uncertainty. The dependent variable is individual income uncertainty in the second half of the sample ($year = 2$), measured as the standard deviation of the unpredicted component of all realized log monthly payroll income in the second year of the two-year sample. In panel A, the independent variables of interest are a donation dummy for donating to the corresponding type of foundations in $year = 1$, the first year of the two-year sample, and income uncertainty in $year = 1$. In panel B, donation dummy$_{year=1}$ is replaced with donation amount$_{year=1}$, the amount donated to the corresponding type of foundations in $year = 1$. Control variables include log income in $year = 1$, log financial wealth in $year = 1$, and demographic variables that include age, age squared, educational attainment, occupational type, marital status, and the number of dependents. All continuous variables except donation amount are standardized, including income uncertainty. Standard errors are clustered at the individual level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.16: Donations and Future Health Shock, by Charity Type

	(1)	(2)	(3)
Dependent variable		Health shock$_{t+2}$	
Charity type	All	Religious	Secular
Panel A: Whether donated in quarter $t+1$			
Donation dummy$_{t+1}$	0.00	-0.01	0.01
	(0.01)	(0.01)	(0.01)
Income uncertainty$_t$	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Observations	222,069	222,069	222,069
R^2-Adjusted	0.433	0.433	0.433
Control variables	YES	YES	YES
Individual fixed effect	YES	YES	YES
City × quarter fixed effect	YES	YES	YES
Panel B: Donation amount in quarter $t+1$			
Donation amount$_{t+1}$	-0.00040	-0.00088	0.00040
	(0.00075)	(0.00093)	(0.00128)
Income uncertainty$_t$	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Observations	222,069	222,069	222,069
R^2-Adjusted	0.433	0.433	0.433
Control variables	YES	YES	YES
Individual fixed effect	YES	YES	YES
City × quarter fixed effect	YES	YES	YES

Notes: The dependent variable is an indicator for experiencing a health spending *shock* in the subsequent quarter, defined as being in the top 50% of non-zero health spending within the quarter (constructed from monthly data aggregated to the quarter via a three-month window). Panel A reports coefficients on an indicator for whether the household donated in quarter $t+1$; Panel B reports coefficients on the raw donation amount in quarter $t+1$ (not standardized). Control variables include health shock dummies in quarters $t+1$ and t, financial wealth, demographic covariates (age and age squared, education, occupation, marital status, and the number of dependents), and in the preceding two quarters. All continuous control variables, including income uncertainty, are standardized. All specifications absorb individual fixed effect and city-by-quarter fixed effects and cluster standard errors at the individual level. Robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.17: Variable Definitions: Field Experiment

Variable	Definition / Construction
Dependent Variables	
Donation dummy	=1 if the user donates; =0 otherwise
Donation amount	USD amount donated in the field experiment, converted from CNY
Per-capita donations(city-level)	The total donations on Platform X per million residents at the prefecture-city level during the experiment period, z-scored
Treatment effect(city-level)	Heterogeneous treatment effects of the field experiment at the prefectural-city level, z-scored
Donor Information	
Treated	=1 if the donation page shows the phrase "accumulate good spiritual connections to receive karmic blessings" beneath the donate button; =0 otherwise
Age	Donor age (years)
Hist. visit case (cumul.)	Number of campaigns the donor had viewed before the experiment
Hist. donate case (cumul.)	Number of campaigns the donor had donated to before the experiment
Hist. donate amt. (cumul.)	Cumulative amount the donor had donated before the experiment, USD
Hist. visit frequency (per year)	Average annual number of campaigns the donor had viewed prior to the experiment, normalized by registration tenure
Hist. donate frequency (per year)	Average annual number of campaigns the donor had donated to prior to the experiment, normalized by registration tenure
Hist. donate amt. (per year)	Average annual donation amount prior to the experiment, normalized by registration tenure, USD
Last month visited(=1)	=1 if donor viewed any campaign in the last 30 days
Last month visited case	Number of campaigns the donor had viewed in the last 30 days
Last month donated count	Number of campaigns the donor had donated to in the last 30 days
Last month donated amt.	Cumulative amount the donor had donated in the last 30 days, USD
Anonymous donation count	Number of campaigns the donor had anonymously donated to before the experiment
Anonymous donation amt.	Cumulative amount the donor had anonymously donated before the experiment, USD
Same city(=Yes)	=1 if donor's IP-prefecture matches beneficiary's prefecture at the city level
Channel(=Timeline posts)	=1 if the donor accessed the campaign via timeline feeds on WeChat

Channel(=Social messages)	=1 if the donator accessed the campaign via messages from social friends on WeChat
Channel(=Direct platform visits)	=1 if the donator directly visit the platform and accessed the campaign on the platform page
Campaign Characteristics	
Campaign target amt.	Fundraising target amount of the campaign, USD
Campaign target amt. (log)	Natural logarithm of Campaign target amt
Campaign word count	Character (word) count of the campaign description
Campaign picture count	Number of pictures on the campaign page
Patient age	Age of the campaign patient (years)
Patient gender(=Male)	=1 if beneficiary gender is male
Insurance coverage(=Yes)	=1 if beneficiary reports any health-insurance coverage
Cancer(=Yes)	=1 if diagnosis is cancer
Regional Context Variables at the Prefecture-city Level	
First principal component of the spirituality-related Baidu search indices	A city-level measure of pre-exposure to spiritual narratives. It is the first principal component derived from a principal component analysis of the 2022 Baidu search index frequency for eight keywords related to traditional beliefs about fate and supernatural forces: "God of Wealth" (cái shén), "Feng Shui" (fēng shuǐ), "auspicious day of the zodiac" (huáng dào jí rì), "warding off evil spirits" (pì xié), "praying for good luck" (qí fú), "burning incense" (shāo xiāng), "karma" (yīn guǒ), and "I Ching/Book of Changes" (zhōu yì), zscored
Per capita gross regional product	Gross regional product per capita, z-scored
Per capita retail sales	Retail sales of consumer goods per capita, z-scored
Per capita public expenditure	Public fiscal expenditure per capita, z-scored
Per capita public expenditure (science and technology)	Fiscal expenditure on science & technology per capita, z-scored
Per capita public expenditure (education)	Fiscal expenditure on education per capita, z-scored
Coverage of urban employee basic pension	Coverage rate of urban employee basic pension insurance (%), z-scored
Coverage of urban employee public health insurance	Coverage rate of urban employee public health insurance (%), z-scored
Coverage of urban employee unemployment insurance	Coverage rate of urban employee unemployment insurance (%), z-scored

Notes: This table defines all variables used in the field experiment analysis. Regional context variables are at the prefecture-city level and z-scored. Monetary values on platform X are converted to USD at the exchange rate.

Table A.18: The Field Experiment: Balance Tests

Covariate	Mean		T-Statistic/Chi-Squared	*p*-Value
	Control	Treated		
Age	38.168	38.179	-1.323	0.186
Hist. visit case (cumul.)	35.848	35.850	-0.054	0.957
Hist. donate case (cumul.)	4.489	4.504	-1.466	0.143
Hist. donate amt. (cumul.)	18.159	18.208	-1.159	0.246
Hist. visit frequency (per year)	8.140	8.139	0.201	0.841
Hist. donate frequency (per year)	1.036	1.039	-0.987	0.324
Hist. donate amt. (per year)	4.357	4.367	-0.641	0.522
Last month visited(=1)	37.6%	37.6%	0.121	0.904
Last month visited case	0.667	0.666	0.931	0.352
Last month donated count	0.078	0.078	-1.641	0.101
Last month donated amt.	0.311	0.313	-0.702	0.483
Anonymous donation count	0.109	0.107	0.971	0.332
Anonymous donation amt.	0.198	0.200	-0.767	0.443
Campaign target amt.	42141.2	42175.3	-1.659	0.097
Campaign target amt. (log)	10.649	10.650	-1.357	0.175
Campaign word count	848.495	848.051	1.424	0.154
Campaign picture count	7.389	7.386	0.963	0.336
Patient age	39.619	39.591	1.466	0.143
Patient gender(=Male)	61.2%	61.2%	0.145	0.885
Insurance coverage(=Yes)	90.1%	90.1%	0.470	0.638
Cancer(=Yes)	25.4%	25.5%	0.216	0.829
Same city(=Yes)	31.9%	31.8%	0.832	0.405
Channel(=*Timeline posts*)	84.0%	84.0%	0.129	0.898
Channel(=*Social messages*)	14.7%	14.7%	0.205	0.838
Channel(=*Direct platform visits*)	1.3%	1.3%	-1.074	0.283

Notes: This table presents the balance test results for the field experiment on Platform X examining the effect of spiritual narratives on the likelihood to donate. Sample balance was tested between observations from the treatment group and control group potential donors. We report group means, t-statistics for continuous variables or Chi-squared statistics for binary variables, and the corresponding p-values. All currency units are converted to USD at the exchange rate.