University of Groningen

Does Market Experience Attenuate Risk Aversion? Evidence from Landed Farm Households in Ethiopia

Melesse, Mequanint Biset; Cecchi, Francesco

Published in:
World Development

DOI:
[10.1016/j.worlddev.2017.05.011](https://doi.org/10.1016/j.worlddev.2017.05.011)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2017

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Melesse, M. B., & Cecchi, F. (2017). Does Market Experience Attenuate Risk Aversion? Evidence from Landed Farm Households in Ethiopia. *World Development*, 98, 447-466.
<https://doi.org/10.1016/j.worlddev.2017.05.011>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Does Market Experience Attenuate Risk Aversion? Evidence from Landed Farm Households in Ethiopia

MEQUANINT B. MELESSE^{a,b} and FRANCESCO CECCHI^{b,c,*}

^a *Bahir Dar University, Ethiopia*

^b *Wageningen University, Netherlands*

^c *University of Groningen, Netherlands*

Summary. — Risk preferences are important drivers of many relevant economic decisions of farm households. High risk aversion is a well-known trigger of “poverty traps” for farm households in developing countries. This paper analyzes the effect of market experience on risk aversion for a relatively large sample of landed farm households characterized by historically low mobility in Ethiopia. We measure risk aversion using lab-in-field experimental data, and relate it to actual market experience of household heads. We use an instrumental variable approach to address the issue of endogeneity due to possible self-selection into trade. We find that market experience attenuates risk aversion—farm households with greater market experience are more risk tolerant. Results are robust to using several alternative specifications, controlling for internal mobility, out-migration and other potential unobservables, and for violations to rational choice. Overall, this study provides strong empirical evidence that risk preferences endogenously change as a result of market experience, and can help design policies aiming to increase the productivity and efficiency of farm households.
© 2017 Elsevier Ltd. All rights reserved.

Key words — endogenous risk preferences, risk aversion, market experience, experimental economics, Ethiopia

1. INTRODUCTION

Risk preferences play an important role in virtually all economic decision of farm households, like the adoption of improved agricultural technologies, the choice of inputs and production of different crops, and long-term investments. Poor farm households in developing countries are often characterized by a high degree of risk aversion (Binswanger, 1980; Dercon, 1996; Franken, Pennings, & Garcia, 2014; Harrison, Humphrey, & Verschoor, 2010; Humphrey & Verschoor, 2004; Wik, Kebede, Bergland, & Holden, 2004). Their allocation decisions typically reflect not only highest expected value opportunities, but also algorithms that minimize risk exposure—as they typically overweight potential losses over potential gains.¹ Accordingly, high expected value opportunities often go unrealized. Ample empirical evidence shows that risk-averse farmers are reluctant to adopt innovations, such as improved agricultural technologies (Alem, Bezabih, Kassie, & Zikhali, 2010; Fafchamps, 2010; Lamb, 2003). Farmers may thus be locked into poverty traps induced by persistent risk aversion (Delpierre, Verheyden, & Weynants, 2016; Dercon & Christiaensen, 2011).

To date, much of the empirical research on risk taking among farm households in developing countries has focused predominantly on the characterization of risk preferences and their coping strategies (for a review and more discussion see Bhattamishra & Barrett, 2010; Dercon, 2008; World Bank, 2014). Traditionally, interventions aiming at changing the high risk aversion nature of farm households have focused mainly on affecting their decision incentives and constraints. Facilitating farm households’ access to insurance markets has typically been the common approach of such interventions. The basic idea is that insurance markets can help farm households to “sell” and transfer risk, correspondingly relaxing their constraints. Evidently, a small but emerging experimental literature has reported results that indicate access to insurance markets induces farm households to take more risk,

allocating more resources to high-return but high-risk agricultural investment and production choices (e.g., Karlan, Osei, Osei-Akoto, & Udry, 2014; Leiva & Skees, 2008).

These findings reflect changes in behavior, but do not address the issue of risk preferences *per se*. Economic literature has long suggested that individual preferences may endogenously change as a result of individual experience (e.g., Stigler and Becker, 1977; Becker & Mulligan, 1997; Netzer, 2009), and that markets can directly affect preferences (e.g., Bowles, 1998; Falk & Szech, 2013; Henrich, Ensminger, McElreath, Barr, *et al.*, 2010). In this paper we investigate whether market experience induces changes in risk preferences of landed farm households in Ethiopia. In particular, we hypothesize that risk aversion may be attenuated by market experience, potentially via reducing the relative weighing of potential losses over gains. This paper contributes to a diverse literature, both empirical and theoretical, trying to grope around the dynamics of preferences.

Several arguments can be found in literature as to why market experience may change risk preferences. First, exposure to trading in markets may constitute a natural “shock” that provides new experience to induce fundamental changes in risk preferences (Becker & Mulligan, 1997; Bowles, 1998; Netzer, 2009). Second, market experience has been found to reduce other behavioral “anomalies”, such as the endowment effect (List, 2003) and revealed-preference violations (Cecchi & Bulte, 2013; List & Millimet, 2008). Third, a property often bestowed on markets is that they may be able to dispel individual biases (e.g., Gode & Sunder, 1993; Jamal & Sunder, 1996; Smith, 1982). Through time, this may in turn induce reduc-

* We would like to thank Erwin Bulte for his excellent comments and suggestions that improved the paper considerably. This work was supported by the Netherlands Organisation for Scientific Research (N. W.O) [grant number 453-10-001, 2011]. Final revision accepted: May 12, 2017.

tions in such biases, driving biased traders to equilibrium. In fact, while Haigh and List (2005) find that professional traders still exhibit behavior consistent with myopic loss aversion (MLA), Feng and Seasholes (2005) show that sophistication and trading experience eliminate investors' reluctance to realize losses, though not their propensity to realize gains. Mayhew and Vitalis (2014) adapt a lab experiment by Gneezy, Kapteyn, and Potters (2003) and find that the MLA effect is all but eliminated by market experience, although their results do not transfer to other settings. List (2004) uses an artefactual field experiment to show that loss aversion adequately organizes behavior among inexperienced consumers, but consumers with intense market experience behave largely in accordance with neoclassical predictions, failing to exhibit a significant overweighting of losses.

We make use of the low-mobility of Ethiopian farm households who possess land rights designed to minimize migration and absentee landlordism—being conditional on active farming and residence within the same community²—to instrument market exposure with distance of their community of residence to the nearest daily markets. We employ context-free experimental measures of risk preferences, using a behavioral game designed to elicit risk aversion due to the overweighting of potential losses over potential gains (see Gneezy & Potters, 1997), which provides us an objective and incentive compatible measure of risk aversion with real payoffs at stake. Our results reveal that market experience robustly reduces risk aversion, as the share of capital invested in a lottery, with a 50% probability of losing half the invested amount and 50% probability of doubling the invested amount, increases. Next to self-selection into trade, we thoroughly address the issues of internal mobility and selective out-migration, which could make establishing causality difficult in studies of this type. Our finding has important implications for policy interventions aiming to spur rural development in poor countries. If market experience mitigates risk aversion, the penetration of markets in remote areas can be an additional important channel to reduce the productivity lag of rural households, directly helping them exit the poverty trap.

The remainder of the paper proceeds in the following order. Section 2 rationalizes the nexus between market exposure and risk preferences. Section 3 describes the setting and Section 4 summarizes our data and identification strategy. We discuss and interpret our results in Section 5. Section 6 subjects our result to a series of sensitivity checks to probe their robustness, while Section 7 briefly presents concluding remarks.

2. ENDOGENOUS RISK PREFERENCES AND MARKET EXPERIENCE

Recent evidence suggests that people's risk preferences can change over time. For example, Cameron and Shah (2015) report an increase in risk aversion after exposure to natural disasters in Indonesia. On the other hand, Voors *et al.* (2012) and Hanaoka, Shigeoka, and Watanabe (2014) document a decrease in risk aversion (i.e., increased risk tolerance) after exposure to civil conflicts in Burundi and natural disasters in Japan, respectively. Eckel, El-Gamal, and Wilson (2009) also report a decrease in risk aversion after exposure to Hurricane Katrina. Taken together, this literature points to the fact that risk preferences may not be as hard wired as previously thought, and that life experiences may change one's willingness to take risks.

Market exposure may also affect risk preferences. Different authors have documented empirical evidence suggesting that

markets play an important role in shaping and influencing preferences in several ways. For example, Henrich *et al.* (2010) find that exposure to markets may promote fairness, cooperation, and the propensity to trust others. List (2003, 2011) shows that market experience plays a significant role in eliminating behavioral anomalies, like the “endowment effect”—the fact that individuals demand much more to give up a good than they would pay to acquire it. The endowment effect, in turn, has often been explained by the existence of loss aversion (e.g., Kahneman, Knetsch, & Thaler, 1990; Thaler, 1980). Coherently, List (2004) finds that inexperienced agents tend to make loss-averse choices that are better explained through prospect theory (Kahneman & Tversky, 1979), while agents with intense market experience behave largely in accordance with neoclassical predictions. This is different from saying that market experience changes peoples' risk preferences, though it partially implies it. In fact, if market experience eliminates the kink in indifference curves around the current endowment (Kahneman & Tversky, 1979), given an investment with constant and positive expected value and constant chances of gains and losses, people should be willing to invest more as they “learn” not to overvalue losses. In other words, the revealed preference for risk increases as people become less loss-averse and start behaving closer to the expected utility hypothesis.

The negative correlation between market exposure and risk aversion has been documented in a variety of settings. For example, Fellner and Maciejovsky (2007) find that high risk aversion and low levels of market activity are systematically related, while Franken *et al.* (2014) show that risk aversion is associated with the choice of more conservative marketing alternatives among American agricultural producers. While suggestive, these studies do not provide conclusive evidence about the causality underpinning such relationships. Arguably, market exposure may be endogenous to risk preferences—more risk-averse agents may self-select out of market exchanges, and vice versa. To the best of our knowledge our study is the first to go beyond documenting simple correlations, and attempt to address the causal relationship between market experience and risk aversion outside the laboratory setting.

3. SETTING

We conduct an experiment involving 532 randomly sampled landed farm households from 179 villages in 18 Kebeles (municipalities) of West Gojjam, in the Amhara Region of Ethiopia. Our subjects were the main income earners in the family (household heads). These individuals often assume the primary responsibility for making important economic decisions, and are more likely to confront major risky choices of their respective households on a continual basis—their livelihood depends on how well they deal with risks. All the households in this study possess a usufruct title on the land they farm. In Ethiopia, land use rights are legally bound to permanent physical residence in the community (Deininger & Jin, 2006), which reduces the mobility of landed household systematically.

Prior to the land reform proclamation of 1975, the major form of land ownership in the sampled communities was the *rist*, a system that bestowed the right of use to land to all descendants of an individual “founding father”. Land usage rights were distributed to individual households, but land was inalienable and inviolable. No individual household could sell their share of land outside the family, but if a household

moved away from the land, the extended family could decide to redistribute land to other family members or new generations. This resulted in historically low mobility and out-migration, and extremely low prevalence of landless tenancy. For example, [Ofcansky and Berry L. \(1991\)](#) estimate that only about 2% of land in West Gojjam were in the hands of tenants prior to the reform.

Partially because of this, the land reform imposed by the Derg in 1975 held little promise of gain for most people in the area and, to a large extent, land usage remained unaffected throughout the Derg regime. While the proclamation provided that anyone “willing to personally cultivate land shall be allotted rural land sufficient for his maintenance and that of his family” ([Rahmato, 1984](#)), Article 19 gave peasants “possessing rights” to the *rist* land they were tilling at the time of proclamation. Evidence from the Ethiopian Rural Household Survey across the country confirms that as of 1995, 36.6% of the total land was acquired through inheritance and purchases made in the pre-reform period ([Kebede, 2006](#)).³ Moreover, the proclamation officially abolished the land market, making it impossible for people from other rural or urban areas to acquire land.

Another land tenure reform took place in 1997, varying significantly from region to region. Importantly, in West Gojjam land reform discontinued the redistribution of land on the basis of household size as practiced in the region and other parts of the country ([Ali, Deininger, & Kemper, 2015](#)). Instead, it separated farmers into *birokrasi* (bureaucrats) and *chequn* (oppressed), and proceeded to reallocate up to 12 *timad* (roughly three hectares, depending on land availability) of land to local *chequn* through a lottery, leaving local *birokrasi* with a maximum of four *timads*. Again, however, land usage rights were conditional on active farming and residence within the same community. While this certainly did not prevent people from moving away from the community, it certainly did create a disincentive to mobility, especially for the *chequn*.⁴ More importantly, in our dataset in-migration is virtually absent for at least twenty-five years—with the exception of inter-community marriages—and all surveyed households belong to historically landed communities under the *rist* system that have resided in the same community for several generations. This is quite important when it comes to our empirical strategy, as self-selection into longer or shorter distance from markets can only plausibly be caused by out-migration, at dear cost of losing all claims on previously farmed land (see further discussion in Section 6).

4. DATA AND EMPIRICAL STRATEGY

(a) *Measuring risk aversion*

Our measure of risk aversion builds on a simple game designed by [Gneezy and Potters \(1997\)](#). [Table 9](#) in the appendix provides the detailed procedure of the game. Subjects were allotted an initial endowment of US\$ 2.8, or around twice the average daily income in the area, as a token of appreciation for their participation in a previous survey.⁵ Subjects were subsequently asked to decide on how much of their endowment to invest in a lottery with 50% probability of doubling and 50% probability of halving the invested amount. The experiment was also completely decontextualized and participants did not face any information constraint and uncertainty related to the parameters of the decision—probability and return characteristics of the risky asset.⁶ Following this, we interpret our risk measure as reflecting the risk aversion of participants.

The design of the experiment is such that subjects trade off expected value of a lottery with variance by choosing the amount of budget allocated to a risky asset. In other words, an increase in expected returns could only be procured by increasing risk of losing a large amount. From the point of view of prospect theory, simply put, the higher the loss aversion the lower the budget allocated to the risky asset, while from that of an expected utility framework, the experimental choices can be formally described as follows. The expected value of the risky investment (x) is $E(x) = 0.75x$ and its variance $Var(x) = 0.0625x^2$.⁷ Under expected utility maximization, there is a unique optimum which depends both on the curvature of the utility function and the baseline level of income a household possesses ([Jehle & Reny, 2011](#)). It is relevant to identify how different choices of x map actually into different coefficients of absolute risk aversion. The trade off becomes more favorable for subjects whose risky investment (x) is greater than the threshold of the equality of the expected mean and variance equations, which is about 12 Ethiopian Birr. Thus, the experimental choices exhibit the more plausible decreasing absolute risk aversion (DARA) for subjects who invested an amount greater than the threshold level in the risky asset, given the initial endowments allocated to the subjects.

Great effort was made to ensure that participants understood the details of the experiment. Subjects were fully informed about the objective probabilities of winning and losing, and about the corresponding size of gains and losses. Subjects were made to perceive the same probabilities, and no time limit was imposed. Choices were also private and could not be observed by other subjects. In order to encourage our subjects to consider the decision tasks seriously and reveal their true preferences, we made the implied incentives from our experiments very significant to the participants—the average payoff (58 Ethiopian Birr) was considerably above the opportunity cost of their time.

We use the proportion of the endowment which has not been committed to the risky investment relative to the total endowment as an index of relative risk aversion for each household.⁸ We present the distribution of the risk aversion index in [Figure 1](#). The figure reveals substantial heterogeneity in risk preferences across our sample farm households. While all our subjects chose to invest some positive amount of their endowment in the risk asset (i.e., the maximum of the risk aversion index is less than one), only a small fraction of them chose to put their entire endowment in the risk investment.

Risk preferences have also been shown to be context specific, and some scholars argue that risk preference measures should be framed in a relevant context (see [Dohmen et al., 2011](#); [MacCrimmon & Wehrung, 1990](#)). Despite the fact that experimental approaches produce objective and incentive compatible measures of risk preferences, their drawback is that they are context free. In an effort to complement this limitation, we elicit an additional measure of risk aversion using a survey question in the context of a market decision.

The first two rows in [Table 1](#) present information on these alternative measures of our dependent variable—risk aversion. The first row contains risk preferences as elicited from the risk experiment. The second row presents information on self-reported risk preferences obtained from a simple survey question, which we use as an alternative measure for risk preferences in our robustness checks. We asked respondents to indicate whether they would dare to trade with somebody they didn't know. We then generated a dummy indicator for risk aversion, taking the value one if the household did not dare to trade with strangers, zero otherwise. In both measures, a

Figure 1. Histogram distribution of the risk aversion index for our sample.

Table 1. Summary statistics

Variables	Description	Mean	Std. Dev.	Min	Max
Risk aversion index	Risk aversion coefficient (game)	0.69	0.246	0	0.971
Risk aversion indicator	Risk aversion index (survey)	0.57	0.495	0	1
Market exposure	Market transactions per month	6.46	4.096	0	18
Distance to market (km)	Distance to the nearest daily market	17.40	11.672	1	57
Male	Dummy for male household head	0.92	0.171	0	1
Age	Age in years	43.54	11.448	21	76
Education	Years of education of household head	2.78	3.393	0	13
Household size	People within the household	6.26	2.088	1	17
Land size (timad)	Total cultivable land size	8.21	4.163	2	36.5
Livestock (TLU)	Total Tropical Livestock Units	7.15	4.458	0	35.5
Per capita income	Household per capita income	3187.90	4336.485	520	46150
Village total households	Total number of households in a village	113.31	64.582	45	299

larger score is associated with more risk aversion.⁹ As is evident from the table, the averages of the two indices indicate that farm households are considerably risk averse. This is consistent with earlier evidence on risk natures of farm households in Asia and Africa alike (see Binswanger, 1980; Harrison *et al.*, 2010; Humphrey & Verschoor, 2004; Wik *et al.*, 2004).

We also compute the coefficient of relative risk aversion (CRRA) for our sample in order to put our risk aversion measures in the context of the literature. The computation is done based on the framework of the expected utility theory and a formal exposition of the computation process is presented in Table 10 in the appendix. The estimated range for the CRRA is 1.66–24.12, with a mean of 5.64. This is consistent with what has been reported elsewhere in the literature (e.g., Ait-Sahalia & Lo, 2000; Barsky, Juster, Kimball, & Shapiro, 1997; Jackwerth, 2000; Schechter, 2007). Theory also argues that, under expected utility theory, the levels of risk aversion are extremely high over modest stakes as compared with risk aversion over large stakes (Rabin, 2000; Rabin & Thaler, 2001). However, it is also important to note that the estimates for the coefficients of relative risk aversion may be overinflated, as we consider only daily income from the risk experiment, ignoring income from outside options and associated back-

ground risk and uncertainty in the outcome of risk aversion (Schechter, 2007).

(b) Other variables

We collected data on market exposure and a range of other relevant socioeconomic variables from the sample households. The data contain detailed information on various important aspects of the households (see Table 1). The third row in Table 1 gives information on our key explanatory variable—market exposure—proxied by the average number of transactions of the household in a typical month. It only includes transactions which actually occur at the market. The average household conducts about seven transactions per month. Given our research question, looking at the number of transactions instead of volumes of sales of agricultural products offers several advantages. First, it is market experience that would more likely affect risk preferences, and market experience is more likely to correlate with frequency of transactions rather than with volumes of transactions. Second, households are both buyers and sellers in the market, and number of transactions captures both sides of the market. A commercialization index captures instead only the selling-side of the mar-

ket, since it is typically constructed as a proportion of the volume of the sales of a household relative to its total agricultural produce. Third, it can help to avoid potential skewedness of the data that might happen due to outliers in the volumes of the transactions. This is related to the fact that the percentage of per capita consumption from own agricultural production may be very small for farmers who engage in cash crops.

Nevertheless, we are aware of two caveats that may remain with measuring market experience using the average number of transactions per month. First, the fixed cost of traveling to the market might be greater for those households further away. These individuals may be selling goods of larger value when they travel to the marketplace with a few numbers of transactions, making the potential surplus individuals get from the market a relevant measure for market experience. While we do not have data on the volumes traded unfortunately, we use an indirect (noisy) measure in the form of the estimated total value of own agricultural production sold to examine the correlation between market experience and volumes of agricultural sales. If respondents that sell higher amounts of produce per transaction trade less frequently, then they indeed may be acquiring more experience in virtue of their greater potential surplus. We find that there is no correlation between the two (p -value = 0.377), meaning that there is no evidence that more transactions correspond to greater or smaller transacted volumes, or vice versa. Second, perhaps the cumulative market experience may well be more important than the current monthly average to capture market experience of individuals. We return to this issue in Section 6.

Table 1 contains other explanatory variables as well. Household size was measured by the number of people living under the same roof, sharing production and consumption activities. Livestock was measured using tropical livestock units.¹⁰ The average household has about six family members. It is headed by a person who is about 44 years of age with more than two years of completed schooling. It works on about eight timads¹¹ of cultivable land with a livestock herd of seven tropical livestock units. The average household is resided at a distance of 17 km from the nearest daily market center. The annual average per capita income for the sampled households is about 3188 Ethiopian Birr. We constructed this variable by adding income from all income sources of the household, valu-

ing all agricultural outputs and livestock products at average local prices. Finally, the average village is a home for about 113 farm households, our proxy for village population.

Figure 2 shows the association between the risk aversion index and market exposure. The figure reveals the presence of a clear negative correlation between risk aversion and market exposure, suggesting that market exposure may play a role in explaining the systematic heterogeneity in risk preferences. However, such correlation between risk aversion and market exposure should not necessarily be interpreted as causation. Causal inference necessitates accounting for several potential sources of biases (see below). To attenuate these concerns, we employ an instrumental variables approach in our analysis.

(c) Empirical strategy

Since we are interested to estimate the effect of market exposure on risk aversion of farm households, we set out to estimate the following regression equation:

$$R_i = \beta_0 + \beta_1 M_i + \beta_2 X_i + \varepsilon_i \quad (1)$$

where R_i represents our coefficient of relative risk aversion from our experiments for household i , M_i is our measure of market exposure for household i , X_i is a vector of household covariates, and ε_i is the random error term of the equation. Based on the literature, we identify household covariates that explain risk preferences of individuals, including household size, income level, age, education, a dummy for gender, household land size, and livestock ownership. As our hypothesis is that market experience reduces the overweighting of losses over gains, in turn reducing risk aversion, we expect β_1 to be negative.

As mentioned before, market exposure may be endogenous in our risk preference model of Eqn. (1). For example, the causal relationship may go in the reverse direction. Perhaps, there may also be omitted variables, such as entrepreneurship, that might trigger some self-selection process by driving both risk preferences and market exposure. We adopt an instrumental variables (IV) approach and identify exogenous variation in our market exposure variable to attenuate potential endogeneity concerns. Specifically, we estimate the following two-stage model that simultaneously helps to identify the determinants

Figure 2. Risk aversion and market exposure.

Figure 3. Path diagram of the empirical strategy.

of market exposure and its causal impact on risk preferences of our households:

$$R_i = \beta_0 + \beta_1 M_i + \beta_2 X_i + \varepsilon_i, \text{ and} \quad (2)$$

$$M_i = \alpha_0 + \alpha_1 Z_i + \alpha_2 X_i + u_i \quad (3)$$

where Z_i is a vector of valid instrumental variables, u_i is the random error term of the first-stage regression, and other variables are as explained in Eqn. (1). As often, the real challenge is to find credible instrumental variables Z_i . In principle, appropriate instruments are variables that explain the market exposure of households, but do not affect risk preferences of these households through any other alternative channel, except via market exposure. This amounts to the condition that the instrumental variables must not be correlated with the error term of our risk preference model.

We followed the guidance from the literature in our efforts to identify valid instrumental variables. For example, prior research establishes that geographical factors are key determinants of market exposure decisions of farm households (Barrett, 2008). Distance to potential markets is among the most important geographical factors that determine transaction costs associated with accessing markets (Bedemo, Getnet, & Kassa, 2013; Renkow, Hallstrom, & Karanja, 2004). While distances to markets are exogenous to a large extent to decisions of farm households, one potential concern is that distance to markets may interact with migration, and thus be endogenous as well. Accordingly, issues of mobility and selective migration might present natural confounds against causal inference from our results. We specifically selected our sample to minimize this occurrence, and further probe the robustness of our results for this possibility as a part of our sensitivity analysis in Section 6. On the other hand, there is no obvious argument that systematically links risk preferences and distances to markets. In light of this discussion, distance to daily markets measured from household residence can go arguably well with the admissibility of the exclusion restriction to provide valid instrument for market exposure. Figure 3 presents a graphical representation of our empirical strategy in the form of a path diagram, with distance to markets as instrumental variable for market exposure.

We use a series of tests to inspect whether distance to markets is an appropriate instrument for market exposure. First, we estimate an OLS model explaining variation in market exposure and check whether distance to markets significantly correlates with market exposure in our data. Second, we estimate a regression model to learn what explains variation in our risk aversion index, and check that distance to markets does not enter significantly when we control for market exposure. Finally, we carry out a series of sensitivity checks to establish the robustness of the main results.

5. RESULTS

We proceed in several steps to establish the causal effect of market exposure on risk preferences. It is important to note that the main discussions of the paper are based on the risk aversion index from the risk game.¹² Tables 2 and 3 provide

Table 2. Market exposure reduces risk aversion

Variable	Risk aversion index (OLS)		
	(a)	(b)	(c)
Market exposure	−0.021*** (0.002)	−0.017*** (0.004)	−0.016*** (0.005)
Male			−0.137*** (0.049)
Age			0.018*** (0.005)
Age square			−0.0002*** (0.0001)
Education			−0.030*** (0.003)
Household size			−0.012* (0.005)
Land size			0.002 (0.003)
Livestock			−0.001 (0.002)
Log per capita income			0.013 (0.011)
Village total households			0.0001 (0.0001)
Distance to market (km)		0.0013 (0.002)	0.0003 (0.001)
Constant	0.818*** (0.019)	0.777*** (0.052)	0.487*** (0.158)
Adjusted R^2	0.12	0.12	0.39
F -test	71.69 (1, 530)	36.19 (2, 529)	31.85 (11, 520)
P -value	0.000	0.000	0.000
N	532	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; km stands for kilometer; N stands for the number of observations.

a series of diagnostic simple regression results. Table 2 summarizes results showing the effects of market exposure on risk preferences based on estimates of a series of simple OLS regressions.¹³ We start by estimating a more parsimonious specification (column (a)) with market exposure as the only regressor, and gradually include other household covariates to reach the full specification of the model (column (c)). The most parsimonious specification of the model suggests the presence of a negative and significant correlation between risk aversion and exposure to markets. In the column designated by (b), we go on to controlling for distance to markets at household level—the variable that will later be used as our instrument for market exposure. While the magnitude of its coefficient decreases from −0.021 to −0.017, market exposure still remains significant at 1% level. However, distance to market does not enter significantly in the model. Market exposure again remains significant even when we control for other household covariates to reach at the most elaborate specifications of the model (column (c)), though its coefficient decreases further to −0.016. On average, one standard deviation increase in market exposure results in a 1/3 of a standard deviation decrease in risk aversion.

Our regression results from the most elaborate specifications of the model show that risk preferences of farm households are correlated to a range of other household covariates. Consistent with the literature, male-headed households are less risk averse. This may reflect obvious gender differences in economic resources and opportunities in developing countries. Risk aversion also decreases with education. Similarly, risk

Table 3. *Distance to market and altitude significantly correlate with market exposure*

Variable	Market Exposure (OLS)		
	(a)	(b)	(c)
Male		-0.021 (0.462)	-0.004 (0.459)
Age		0.088* (0.051)	0.089* (0.051)
Age square		-0.001* (0.001)	-0.001* (0.001)
Education		0.005 (0.027)	0.003 (0.027)
Household size		0.050 (0.044)	0.049 (0.044)
Land size		0.369*** (0.024)	0.361*** (0.024)
Livestock		-0.061*** (0.019)	-0.060*** (0.019)
Log per capita income		0.647*** (0.096)	0.642*** (0.095)
Village total households		0.001 (0.001)	0.001 (0.001)
Distance to market (km)	-0.288*** (0.009)	-0.173*** (0.010)	-0.172*** (0.010)
Altitude			-0.0003*** (0.0001)
Constant	11.472*** (0.183)	-0.101 (1.492)	0.607 (1.507)
Adjusted R^2	0.67	0.80	0.81
F -test	1093.34 (1, 530)	220.44 (10, 521)	203.48 (11, 520)
P -value	0.000	0.000	0.000
N	532	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; km stands for kilometer; N stands for the number of observations.

aversion diminishes with household size.¹⁴ The age of the head also matters for risk preferences of a farm household, as risk aversion increases significantly with age but there is a threshold to this relationship. We speculate that this result indicates that people tend to be conservative as age increases, since they have low earning power and less time to recover from losses caused by their involvement in potentially risky ventures. However, this relationship is non-linear as age square enters significantly negative, indicating that people would instead become risk lovers when they get too old, consistent with Kabir and Shakur (2014).

Unfortunately, per capita income does not correlate significantly with risk aversion, which merits some discussion. Risk aversion and market exposure are expected to independently correlate with income. Indeed, there is a strong relationship between market exposure and income in our data (see Table 3 below). As a first order concern, while it is highly likely that income is also partly endogenous, one would argue that the income effect on risk aversion, and the endogeneity of income, might be more important than the independent relationship between market exposure and risk aversion if the simultaneity issue is addressed properly in our model. To attenuate this concern, we estimate our risk aversion model excluding the market exposure variable. However, per capita income does not still enter significantly in the model (see column (a) in Table 11 in the appendix).

An alternative concern can be that it is not average income that should matter but rather the distribution of income. We

test this idea by including an income dummy (one for higher than median income) and per capita income does not still correlate significantly with risk aversion, both when market experience is included (column (b)) and excluded (column (c)) in Table 11. A final potential explanation for the lack of association between risk aversion and per capita income could be that income is poorly measured. Despite all the careful efforts taken, it is hard to properly measure income in the African rural context, partly because it is not stable. With this reservation, we argue that the effect of market exposure on risk aversion is independent to the correlation between market exposure and income (see also Section 6).

However, as has already been indicated, market exposure may be endogenous. To attenuate this concern, we use an instrumental variable (IV) approach to tease out a causal relationship by identifying an exogenous variation in our market exposure variable. We use distance to markets at household level as our instrument for market exposure. Before running our IV models, we now turn to subjecting our instrument to statistical tests to probe its credibility for being a valid instrument. Note that the first criterion for a valid instrument is that it should not be correlated with potential outcomes. This criterion is effectively met in our data as our instrumental variable is not correlated with our risk aversion index across different specifications (see Table 2).

The second criterion for a valid instrument is that it should be significantly correlated with the endogenous explanatory variable. In order to inspect our choice of the instrument in light of this criterion, we next seek to explain what factors determine market exposure of farm households. To do so, we estimate an OLS model, and the results of the regression are presented in Table 3. The results support our choice of the instrumental variable. As expected, distance to market is negatively and significantly associated with market exposure. Distance to markets mirrors transaction costs. Age of the head, age square, land size, livestock, and per capita income are other significant determinants of market exposure. Age, land size, and per capita income are positively correlated with market exposure of a household as expected. Age has a non-linear association with market experience. People in rural areas would travel less frequently to market, as it would become difficult to travel longer distance on foot when they got older. However, livestock enters with unexpected sign in the market exposure model. Perhaps, this could be explained by the role of livestock as a self-insurance risk coping strategy, where relatively self-sufficient households, who would not conduct more exchanges owing to their self-sufficiency, possess a considerable number of livestock both as a buffer and to carry out their agricultural activities.

Against the background of these qualifications, we proceed to estimating 2SLS model (Table 4). Our instrumented market exposure still enters negatively and significantly in the model of risk aversion (column (a)). Now, the direct effect of market exposure on risk preferences dominates a potential reverse effect in explaining the correlation between the two variables, as our instrumental variable estimate isolates the effect of market exposure on risk preferences. The coefficient of the instrumented market exposure is slightly greater than its corresponding value in the fully elaborated OLS model, though it is smaller than the coefficient of market exposure in the parsimonious OLS specification. A potential explanation for such difference is measurement error in market exposure, as expected in typical retrospective data measurements from rural household surveys. While measurement errors can bias OLS coefficients toward zero (Theil, 1971: p. 608), instrumental variable approaches often mitigate such prob-

lems (Gujarati, 2003: p. 527). Supporting this explanation, the standard deviation of the raw market exposure (4.096) is larger than that of its predicted value used in the second stage regression (3.649).¹⁵

All standard tests for valid instruments indicate that our instrument is valid and strong. As has already been shown in Table 3, our instrument is significant in the first-stage regression, and the associated partial F-statistic for the model with only the instrument as an explanatory variable (see Table 3(a)) is way above the minimum 10 threshold value of the “rule of thumb” for strong instruments (Staiger & Stock, 1997). Table 4 also provides further qualifications for strength of our instrumental variable. We probe more formally whether the 2SLS model meets statistical requirements of the over-identification test. We employ “altitude” at the residence of the household as an additional instrument. Altitude can influence access to markets as it captures differences in terrain and hence the quality of the paths/roads to markets. However, it is not *a priori* evident that the exclusion restriction is satisfied with respect to altitude (Pighin *et al.*, 2012). We view this as empirical question and let the data speak. The first-stage regression (column (c) in Table 3) shows that altitude is significantly correlated with market experience.¹⁶ The corresponding 2SLS results are contained in Table 4(b) and the results indicate that the instrumented market exposure variable enters again negatively and significantly. The IV-diagnostics further show that the instruments are relevant. The Sargan test for the 2SLS model fails to reject the null hypothesis that our over-identifying restrictions are valid (p -value = 0.624). We thus contend that our instrumentation strategy is credible, and our results reveal that market exposure is a key determinant of risk preferences of farm households.

Finally, our instrument variable, distance to market, is measured at the household level. We include Kebele fixed effects to examine the extent of Kebele variations in our instrumental variable. This is particularly interesting since the regressions don't include many community-level variables owing to absence of community-level data. The associated results are contained in Table 4 column (c). The results remain significant and quantitatively similar, indicating that most of the variations in the instrumental variables are identified rightly at the household level, and they don't reflect other Kebele-level characteristics. This again provides evidence about the admissibility of the exclusion restriction.

To what extent can we be confident that our results are indeed true effects? We use Maniadis, Tufano, and List (2014)'s theoretical framework to get insights into the robustness of our results. The framework highlights that the decision about whether to recognize a finding as noteworthy should be based on the estimated probability that the finding, made upon reaching statistical significance, represents a true association. This Post-Study Probability (*PSP*) depends on the observed p -value, the power of the design, the prior probability of the hypothesis, and the competition among researchers investigating the research question. Mathematically, the *PSP* is equal to the number of true associations which are declared true divided by the total number of all associations which are declared true, and is given by:

$$PSP = \frac{(1 - \beta)\pi}{(1 - \beta)\pi + \alpha(1 - \pi)}$$

where π represents the fraction of the true associations from the total number of scientific associations examining the hypothesis, α is the statistical significance level, and $1 - \beta$ denotes the power of the experimental design. To provide some insight on how influential our finding should be in

changing our research priors, Table 12 in the appendix presents *PSP* estimates, given the statistical significance level of our result ($\alpha = 0.01$) and the power of our design ($1 - \beta = 99\%$). Since it is difficult to specify a prior π exactly, we consider a range of plausible values (from a low prior to a relatively higher prior) as related to *initial* declared research findings. The results show that it is less likely that the *PSP* for our study is less than 0.5 even for the lower ranges of prior probabilities. However, our *PSP* estimates do not account for researchers' competition, the research specific bias that tends to produce false positives, and the possible interaction between competition and bias. Therefore, the estimates can only be interpreted as an upper bound.

Another key reason for false positives is multiple hypothesis testing (MHT). Following List, Shaikh, and Xu (2016), we report standard errors corrected for multiple outcomes. We use the risk aversion index and CRRA as different outcome, since we do not have credibly different outcomes in our data. While the risk aversion index and CRRA may not be considered as two strictly distinct outcomes, they are not linearly correlated and can shed some insight on jointly identifying treatment effects. For this purpose, we restructure market exposure as a treatment dummy (one for higher than median). Table 13 in the appendix shows the corresponding results based on different approaches of the MHT. The p -values for both multiplicity-unadjusted (column 3) and multiplicity-adjusted (columns 4 across 6) indicate that the results remain quite robust even when we take into account the multiplicity of the comparisons.

Several other features of our study can contribute to increasing the likelihood of our findings to be a real effect. First, our findings are based on a relatively large sample of non-student subjects. Second, the coefficient of market exposure has a reasonably narrow confidence intervals (-0.027 , -0.009), increasing further the probability of detecting a real effect. Importantly, the intervals remain on the same side (negative) of the association axis. Third, our research design has a good power of detecting a range of effect sizes. For example, given the sample size and the distribution of our outcome variable, our study would be able to detect a small effect size of 0.15 with a power of 86% at 5% level of statistical significance.

6. SENSITIVITY ANALYSIS

(a) Accounting for internal mobility and migration

As has been brought forth in the methodology section, internal mobility and migration may cause a concern for self-selection that can impair our causal inference. While distances to markets are to a large extent exogenous to decisions of farm households, one concern is related to the sample selection potentially caused by out-migration. Another potential concern is that distance to markets may interact with internal mobility—i.e., households relocate closer to markets but remain within the same area as to not lose farming rights on land. Both out-migration and internal mobility may serve as mechanisms for farm households to get near to markets, and households involved in mobility and migration are obviously not randomly drawn from the general population. We thoroughly address this concern as follows.

Selective migration out of rural communities is a well-known threat to causal inference in non-randomized as well as randomized settings. To address this concern, our first effort was to purposely base our household sampling on land holding—sampling only landed households. The Ethiopian Land

Proclamation has made enjoying secure and continuous land use rights contingent on permanent physical residence in the community (Deininger & Jin, 2006). We also confirmed our intuition that landed households are less prone to migration through focus group discussions. Finally, we formally test the robustness of our results to the most conservative assumptions about out-migration patterns, as well as internal mobility within the area of the study.

We rely on focus group interviews to learn about the nature of migration over the last five years. The focus group discussions were held at a Kebele level. Each village in the Kebele was represented by a discussant. The group of discussants also included a focal discussant from the Kebele administration office. Totally, 179 villages were included in the group discussions, with an average of 10 villages per Kebele. The average five-year rate of out-migration for all Kebeles in our study was found to be 2.52%, ranging from 0.23% to 4.96%. Consistent with our choice to only study landed households, all focus groups cited landlessness as the number one important reason when asked about the causes of out-migration in their community. Elsewhere, evidence also shows that landlessness is the main driver of rural-urban migration in Ethiopia (Ezra & Kiros, 2001; Hunnes, 2012; Mberu, 2006). This has also been corroborated by our data from the focus group discussions: 98% of the out-migrated households either did not have land at all or had less than 0.25 hectares (one timad) of land before their migration.¹⁷ Note that because of the land reform of 1997, these households were either not part of the ancestral *rist* system of land tenure (e.g., in-migrated more recently) or might have been labeled as part of the *birokrasi* at the time of land redistribution.

We present the relationship between the out-migration rates and average distance to markets at Kebele level in Figure 4. From the figure, we read a tendency for a positive association between distances from markets and out-migration. In other words, it seemed that more remote municipalities have slightly higher rates of out-migration. However, this correlation is not statistically significant ($p = 0.375$).

We proceed to test the impact of selective out-migration on our results more rigorously. In order to control for potentially selective attrition through migration, we run “placebo” regressions by including hypothetical households who migrated and had very low risk aversion. Facing a missing data problem, we

Table 4. Instrumenting market exposure by distance to market and altitude

Variable	Risk aversion index (2 SLS)		
	(a)	(b)	(c)
Market exposure	-0.018*** (0.005)	-0.019** (0.006)	-0.019*** (0.006)
Male	-0.137*** (0.029)	-0.137*** (0.049)	-0.137*** (0.048)
Age	0.018*** (0.006)	0.018*** (0.005)	0.018*** (0.005)
Age square	-0.0002** (0.0001)	-0.0002*** (0.0001)	-0.0002*** (0.0001)
Education	-0.030*** (0.004)	-0.030*** (0.003)	-0.029*** (0.003)
Household size	-0.012** (0.004)	-0.012** (0.005)	-0.011** (0.005)
Land size	0.003 (0.005)	0.003 (0.004)	0.003 (0.004)
Livestock	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Log per capita income	0.015 (0.011)	0.015 (0.012)	0.017 (0.013)
Village total households	0.0001 (0.0001)	0.0001 (0.0001)	0.00004 (0.0001)
Constant	0.487*** (0.162)	0.482*** (0.157)	0.415** (0.171)
Kebele fixed effects			Yes
Sargan test: χ^2 (1)		0.24	
P-value		0.624	
N	532	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; km stands for kilometer; N stands for the number of observations.

use the out-migration rates of each Kebele to place bounds on our estimates of the effects of market exposure on risk aversion. Specifically, we examine if our results would survive the most conservative check for out-migration by hypothetically creating households. The number of households to be artificially created is determined by the out-migration rates of the respective Kebeles, and this process results in 20 such new households. The working assumption is that out-migrated households are more likely to be the highly risk tolerant ones. Accordingly, we proceed by assigning the lowest

Figure 4. Out-migration rates and average distance to markets.

value of risk aversion index (i.e., zero) to these households. All other variables are valued at their respective averages.¹⁸ This approach allows us to place bounds on our estimates without making additional untestable distributional assumptions (Gerber & Green, 2012). We estimate our standard model after making these adjustments to our data. The 2SLS results reported in Table 5. Column (1a) contains second-stage results. The results survive this conservative sensitivity check for out-migration and remain statistically robust.

Next, we probe the robustness of our results for internal mobility, i.e., mobility within the community. Some of the group discussants revealed that it is not uncommon for households to move within their Kebeles to reside near to markets.¹⁹ Following this suggestion, a careful investigation of our data has resulted in 92 households who have not resided in the same location in their community since their establishment. In other words, these households have moved within their village and/or Kebele, rather than migrated away from their community. We employ a series of robustness checks to investigate the possibility that these households might have moved to be near to markets, and whether this could affect our results. First, we probe if our results would withstand the most conservative check through residing these households to the possible farthest villages to markets in their Kebeles.²⁰ Second, we replace market distance measured from the residence of households by market distance measured from the center of their village for each household, and estimate our standard models (reported standard errors are clustered at village level).

The results for both checks are given in Table 5 2SLS (2) and 2SLS (3), respectively. The 2SLS results for the first check are shown in column (2a), while column (3a) provides the 2SLS results for the second check. The results are once again robust, and the related statistical tests presented in the respective (b) columns are satisfied well.

As alternative robustness check, we drop the 92 households, and estimate our models based on information only from households who have resided at the same place since their establishment. This would help us to assess if our results shake for the exclusion of these households. Column (1a) of Table 6 provides the IV estimation results, and the corresponding first-stage regression results are in column (1b). The results remain robust and consistent with our results from Table 4, indicating that our results are not driven by the inclusion of within community migrants. The important test statistics are also quite satisfactory.

Finally, we follow a recent literature facing a similar problem of selective mobility (Callen, Isaqzadeh, Long, & Sprenger, 2014; Hanaoka *et al.*, 2014), and estimate our standard models by including a within-community mobility dummy, indicating that a household has not resided at the same location since its conception, and see if it would enter significantly. We also include an interaction term between the mobility dummy and distance to markets in the market exposure model (first-stage regression) to allow for the possibility that the effect of distance to markets might vary with the status of internal mobility. Column (2a) of Table 6 pre-

Table 5. Robustness analysis for out-migration and internal mobility

Variable	2 SLS (1): 5 Years		2 SLS (2)		2 SLS (3) ^a	
	Risk aversion index		Risk aversion index		Risk aversion index	
	(a)	(b)	(a)	(b)	(a)	(b)
Market exposure	-0.013** (0.007)		-0.014** (0.007)		-0.020*** (0.007)	
Male	-0.138** (0.058)	-0.023 (0.454)	-0.137*** (0.049)	0.251 (0.492)	-0.137*** (0.049)	0.096 (0.498)
Age	0.003 (0.006)	0.078 (0.049)	0.018*** (0.005)	0.046 (0.054)	0.018*** (0.005)	0.065 (0.055)
Age square	2.16e-06 (0.0001)	-0.001* (0.001)	-0.0002** (0.0001)	-0.0004 (0.0006)	-0.0002*** (0.0001)	-0.0007 (0.0006)
Education	-0.031*** (0.003)	0.004 (0.026)	-0.031*** (0.003)	0.010 (0.029)	-0.030*** (0.003)	-0.016 (0.029)
Household size	-0.012** (0.007)	0.051 (0.044)	-0.013** (0.005)	0.063 (0.047)	-0.012** (0.005)	0.079* (0.048)
Land size	0.003 (0.005)	0.370*** (0.024)	0.001 (0.004)	0.408*** (0.025)	0.004 (0.004)	0.401*** (0.026)
Livestock	0.0004 (0.003)	-0.059*** (0.019)	-0.001 (0.002)	-0.058*** (0.020)	-0.001 (0.002)	-0.070*** (0.021)
Log per capita income	-0.009 (0.015)	0.634*** (0.093)	0.008 (0.013)	0.881*** (0.098)	0.017 (0.013)	1.081*** (0.094)
Village total households	0.0001 (0.0002)	0.001 (0.001)	0.0001 (0.0001)	0.002 (0.001)	0.0001 (0.0001)	-0.0023* (0.001)
<i>Instrument</i>						
Distance to market (km)		-0.174*** (0.009)		-0.120*** (0.008)		-0.024*** (0.002)
Constant	0.922*** (0.184)	0.194 (1.444)	0.528*** (0.160)	2.728* (0.710)	0.468*** (0.161)	-3.814** (1.553)
First stage <i>F</i> -test		230.51		188.85		183.18
Market exposure		(10, 541)		(10, 521)		(10, 521)
<i>P</i> -value		0.000		0.000		0.000
Adjusted <i>R</i> ²		0.80		0.78		0.77
<i>N</i>	552	552	532	532	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; km stands for kilometer; *N* stands for the number of observations; ^areported standard errors are clustered at village levels.

sents the 2SLS results. However, both the mobility dummy and its interaction with distance to markets do not correlate significantly with market exposure (column (2b)). While it may not be so informative given the first-stage results, we simply include the interaction term in our set of instruments to inspect the sensitivity of the main results.²¹ Our main result remains largely robust (columns (2a)), and key over-identification test statistics also indicate that the over-identification restrictions are valid.

(b) *Further robustness checks*

We estimate several alternative models in an effort to probe further the robustness of our results. In Table 7, we present a series of IV results. We first inspect the robustness of our results to an alternative proxy for risk preference. We use a dummy indicator for risk aversion from a survey question to capture the context of the market decision environment of our subjects. We specifically asked households whether they would dare to trade with whom they did not know. Following the binary nature of our dependent variable, we estimate an IV probit model and report marginal effects. As often, we esti-

mate the IV probit model in two steps. In the first step, an OLS model is estimated for market exposure using distance to markets and altitude—our instruments—as exclusion restrictions for identification purpose. We then include both the predicted market exposure and the generated generalized error term as explanatory variables in our probit model. We include the generalized error term to account for any potential endogeneity that might be driven by unobserved heterogeneity. The results are contained in column (1a), while the associated first-stage results of the model are presented in column (1b) (Table 7). There is again a robust correlation between predicted market exposure and our risk aversion indicator. Moreover, the generalized residual term does not enter significantly, implying that there are no common unobserved factors that drive both market exposure and risk aversion.

We provide additional robustness checks in Table 7. In columns (2a) and (3a), we examine if our results are robust to omission of per capita income and inclusion of “rationality”. As has already been discussed in Section 5, our main result might be contaminated by the so-called multicollinearity statistical problem, as (most of) our covariates are well known and non-trivial predictors of income levels in the literature.

Table 6. *Robustness analysis for internal mobility*

Variable	2 SLS (1)		2 SLS (2)	
	Risk aversion index		Risk aversion index	
	(a)	(b)	(a)	(b)
Market exposure	−0.019*** (0.006)		−0.019*** (0.006)	
Male	−0.134** (0.055)	−0.063 (0.496)	−0.137*** (0.048)	−0.025 (0.463)
Age	0.018*** (0.006)	0.059 (0.056)	0.018*** (0.005)	0.088* (0.051)
Age square	−0.0002** (0.0001)	−0.001 (0.001)	−0.0002*** (0.0001)	−0.001* (0.001)
Education	−0.031*** (0.003)	−0.008 (0.028)	−0.031*** (0.003)	0.005 (0.027)
Household size	−0.013*** (0.005)	0.021 (0.046)	−0.012** (0.005)	0.051 (0.045)
Land size	0.004 (0.004)	0.366*** (0.025)	0.003 (0.004)	0.369*** (0.024)
Livestock	−0.0008 (0.0022)	−0.042** (0.020)	−0.001 (0.002)	−0.061*** (0.019)
Log per capita income	0.016 (0.013)	0.574*** (0.098)	0.015 (0.012)	0.648*** (0.096)
Village total households	0.0001 (0.0002)	0.0002 (0.002)	0.0001 (0.0001)	0.0007 (0.0013)
Internal mobility dummy			−0.043* (0.022)	0.064 (0.377)
<i>Instruments</i>				
Distance to market (km)		−0.178*** (0.010)		−0.172*** (0.010)
Distance to market (km) * Internal mobility dummy				−0.006 (0.018)
Constant	0.472*** (0.173)	1.243 (1.597)	0.484*** (0.156)	−0.125 (1.497)
Sargan test:				
χ^2 (1)			0.26	
P-value			0.610	
First stage F-test		196.77		183.05
Market exposure		(10, 429)		(12, 519)
P-value		0.000		0.000
Adjusted R ²		0.82		0.80
N	440	440	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; km stands for kilometer; N stands for the number of observations.

Table 7. *Alternative measure of risk preferences and Omitted variable bias*

Variable	IV Probit model (1)		2 SLS (2)		2 SLS (3)	
	Risk aversion indicator		Risk aversion index		Risk aversion index	
	(a)	(b)	(a)	(b)	(a)	(b)
Market exposure	−0.178*** (0.046)		−0.015*** (0.004)		−0.018*** (0.006)	
Male		−0.021 (0.462)	−0.137*** (0.049)	−0.023 (0.482)	−0.135*** (0.048)	−0.072 (0.457)
Age	0.081** (0.040)	0.088* (0.051)	0.018*** (0.005)	0.085 (0.053)	0.018*** (0.005)	0.084* (0.051)
Age square	−0.0008* (0.0004)	−0.001* (0.001)	−0.0002*** (0.0001)	−0.001* (0.001)	−0.0002*** (0.0001)	−0.001* (0.001)
Education	−0.090*** (0.022)	0.005 (0.027)	−0.030*** (0.003)	0.028 (0.028)	−0.030*** (0.003)	−0.002 (0.027)
Household size	−0.007 (0.037)	0.050 (0.044)	−0.014*** (0.005)	−0.037 (0.044)	−0.012** (0.005)	0.039 (0.044)
Land size	−0.018 (0.031)	0.369*** (0.024)	0.002 (0.004)	0.408*** (0.024)	0.002 (0.004)	0.378*** (0.024)
Livestock	−0.006 (0.016)	−0.061*** (0.019)	−0.0003 (0.002)	−0.034* (0.019)	−0.001 (0.002)	−0.063*** (0.019)
Log per capita income	0.070 (0.094)	0.647*** (0.096)			0.016 (0.002)	0.590*** (0.096)
Village total households	0.001 (0.001)	0.001 (0.001)	0.0001 (0.0001)	0.0005 (0.001)	0.0001 (0.0001)	0.001 (0.001)
Generalized Residual	0.056 (0.093)					
Rationality					0.002 (0.002)	−0.054*** (0.014)
<i>Instrument</i>						
Distance to market (km)		−0.173*** (0.010)		−0.206*** (0.009)		−0.170*** (0.010)
Constant	−0.761 (1.099)	−0.101 (1.492)	0.589*** (0.131)	5.323*** (1.311)	0.464*** (0.157)	0.680 (1.489)
First stage <i>F</i> -test		220.44		220.97		206.65
Market exposure		(10, 521)		(9, 522)		(11, 520)
<i>P</i> -value		0.000		0.000		0.000
Adjusted <i>R</i> ²		0.80		0.79		0.81
Log likelihood	−1293.78					
Prob. > χ^2	0.000					
<i>N</i>	516	532	532	532	532	532

Robust standard errors in parentheses; **p* < 0.10, ***p* < 0.05, ****p* < 0.01; km stands for kilometer; *N* stands for the number of observations.

We then estimate our standard model excluding per capita income. Columns (2a) and (2b) give, respectively, the second-stage and the corresponding first-stage results, once per capita income is excluded. Altogether, the results indicate that our main results remain largely robust.

As per rationality, the literature articulates that rationality of individuals is a strong correlate of their market experience (Cecchi & Bulte, 2013; List & Millimet, 2008). We left rationality out from our initial analysis for this obvious endogeneity problem. We now include “rationality” as a covariate in our basic risk aversion models.²² As is evident from the second-stage regressions (column (3a) of Table 7), our results show again a robust correlation between instrumented market exposure and our risk aversion index. Consistent with the literature, market experience and rationality violations are negatively correlated (first-stage regression). However, rationality does not enter significantly in our risk aversion model: more rational people do not have significantly different risk preferences than those behaving less rationally.

In Table 8, we report a series of robustness results related to distance to markets –our instrument, and market exposure –our key explanatory variable. First, we change our measure

of distance to markets. We now use distance to markets measured by travel time instead of kilometers. The reason for the change is that distance measured by travel time may better reflect differences in terrain and the quality of roads to markets. Alternatively, it may also help to attenuate potential measurement errors, as it indicates the travel time taken for households accounting for the nature of the terrain. Column (1a) of Table 8 provides second-stage results. The results are again quite comparable to what we have already obtained in Section 5. The associated first-stage results are given in column (1b). The relevant test statistics also indicate that our instrumentation approach is appropriate.

Unobserved heterogeneity is another remaining potential concern in our causal identification effort. Distance from the market could impact risk preferences for a host of different reasons other than through individuals’ market experience. Specifically, market distance may reflect non-market attributes that can challenge the exclusion restriction between distance to market and risk aversion. For example, Cameron and Shah (2015) find increases in risk aversion after experiencing natural disasters. Perhaps in this setting, resources dedicated toward helping individuals who suffer from natural threats are harder

Table 8. *Alternative interpretations of distance to market and market experience*

Variable	2 SLS (1)		2 SLS (2)		2 SLS (3)	
	Risk aversion index		Risk aversion index		Risk aversion index	
	(a)	(b)	(a)	(b)	(a)	(b)
Market exposure	−0.018*** (0.006)		−0.020*** (0.007)			
Cumulative market experience					−0.0007*** (0.0002)	
Male	−0.137*** (0.048)	−0.115 (0.461)	−0.121** (0.051)	0.143 (0.430)	−0.130*** (0.049)	9.013 (16.664)
Age	0.018*** (0.005)	0.075 (0.051)	0.015*** (0.006)	0.084* (0.047)	0.022*** (0.006)	7.954*** (1.844)
Age square	−0.0002** (0.0001)	−0.001 (0.001)	−0.0001** (0.0001)	−0.001** (0.0005)	−0.0002*** (0.0001)	−0.022 (0.019)
Education	−0.030*** (0.003)	0.012 (0.027)	−0.029*** (0.003)	0.015 (0.026)	−0.032*** (0.003)	−1.610* (0.968)
Household size	−0.012** (0.005)	0.079* (0.044)	−0.008* (0.005)	0.074* (0.041)	−0.011** (0.005)	2.437 (0.043)
Land size	0.003 (0.004)	0.330*** (0.025)	0.002 (0.005)	0.313*** (0.028)	0.003 (0.004)	9.855*** (0.870)
Livestock	−0.001 (0.002)	−0.072*** (0.019)	−0.0009 (0.002)	−0.065*** (0.018)	−0.001 (0.002)	−1.391** (0.690)
Log per capita income	0.014 (0.012)	0.921*** (0.089)	0.012 (0.013)	0.576*** (0.087)	0.013 (0.012)	14.986*** (3.452)
Village total households	0.0001 (0.0001)	−0.001 (0.001)	0.0001 (0.0001)	0.0001 (0.001)	0.0001 (0.0001)	0.015 (0.044)
<i>Instruments</i>						
Distance to market (hrs)		−0.088*** (0.005)				
Distance to market (km)				−0.153*** (0.009)		−4.597*** (0.345)
Constant	0.488*** (0.157)	−0.895 (1.470)	0.549*** (0.162)	0.144 (1.375)	0.307 (0.189)	−266.003*** (53.796)
First stage <i>F</i> -test		222.50		139.98		159.62
Market exposure		(10, 521)		(10, 435)		(10, 521)
<i>P</i> -value		0.000		0.000		0.000
Adjusted <i>R</i> ²		0.81		0.76		0.75
<i>N</i>	532	532	446	446	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; hrs stands for hours; km stands for kilometer; *N* stands for the number of observations.

to obtain when one lives away from a market. Then, individuals living further from the market might be more risk averse regardless of market experience. Another particular concern is that permanent markets are often located in small towns. While none of the households in our sample come from such towns, households residing very close to markets, and hence to these towns, may have larger opportunities for larger social networks, and may in turn be exposed to broader social interactions. For example, [Renkow et al. \(2004\)](#) contend that market distance is definitely much more than geometry. It governs not only access to market information and infrastructure but also relative opportunities for interaction and communication. As a result, people closer to the market might develop personal relationships or interconnected arrangements, suggesting that “shortest” market distances might not capture only market access opportunities. If so, we may not pick only market exposure effects on risk preferences for households residing very close to markets. While the econometric tests suggest that this problem is insignificant, we seek to formally examine this unobserved heterogeneity problem in two ways.²³ First, we throw away 86 households settling at less than six km market distance (i.e., near to the boundaries of the small towns), which can minimize the intensity and opportunities of poten-

tial interactions, and then estimate our model using information only from the remaining households. The results are reported in columns (2a) and (2b), and they are once more robust and consistent with our main results.

Second, we carry out a robustness analysis to unobserved heterogeneity using the standard bounding approach test developed by [Rosenbaum \(2002\)](#). For this purpose, we consider the market exposure variable as a treatment variable and restructure our data to comply with the matching methods of causal inference with observational data. We divide our observations into control and treated groups by using the median market exposure. While the control group comprises farm households with market exposure below the median, farm households with market exposure above the median make up the treated group. This procedure results in 266 households in each of the control and treated groups. We then estimate the propensity scores and use them to match treated households with statistically comparable households from the control group. Matching has been done only on farm households who are on the common support. The Kernel density distributions of the propensity scores for the control and treated groups reveal the presence of a clear overlap between the two groups (see [Figure A1](#) in the appendix). The estimated

average treatment effect (ATE) is found to be -0.0169, and is also quite comparable to our reported results, given our selection process remains valid.

We use the outcomes of the matching process to employ the Rosenbaum's bounding approach for testing the extent of the unobserved heterogeneity problem in our data. This test allows us to assess how strong an unobservable heterogeneity must influence the selection process so as to undermine the causal inference and the results. The results of the Rosenbaum's bounding test are reported in the appendix (Table 14). The test shows that our results (specifically the ATE) are robust to unobservable heterogeneity, even to the extent that would more than double ($\gamma = 2.3$) log odds of differential assignment to treatment, which is highly unlikely in light of the observable heterogeneity in our data.

Finally, in columns (3a) and (3b) of Table 8, we employ a different proxy for market experience. The cumulative market experience may well be more important than the current monthly average to capture market experience of individuals. Perhaps, individuals who have been trading in the market for decades with a lower transaction frequency likely have more market experience than high frequency traders who are new. To formally test this idea, we construct a variable that assumes constant transactions across adult life to generate an estimate of cumulative market experience of individuals, and run our basic model by using this variable instead of the monthly average transaction. Our results are robust and qualitatively replicated, though the magnitude of the coefficient for market experience is considerably lower.

7. CONCLUSIONS AND DISCUSSION

Recent years have witnessed a paradigm shift on the role of markets—from a simple neutral means to allocate resources to active mechanisms that also mediate and influence behavior and preferences of market participants. Yet, “much of the academic research on risk has its balance wrong, focusing too much on admittedly fascinating issues related to risk management and coping mechanisms, but not enough on its implications and the scope for interventions” (Dercon, 2008: p. ii98). In fact, while risk aversion has long been identified as having a detrimental effect on economic development, the scope for policy intervention in this domain has remained limited for a long time. The conventional thinking in the existing literature on risk is to envisage farm households as inherently risk averse. This logic has shifted the focus of the analysis in the literature to examining risk management and coping strategies used by the households (Dercon, 2002; World Bank, 2014). Whether policy can have a role in shaping risk preferences of farm households, and thereby their investment decisions, largely depends on our understanding of what determines risk preferences and thus their change.

The obvious endogeneity between risk preferences and the extent to which a person is exposed to markets has limited the capacity of previous studies to draw clear conclusion with

respect to the directionality of their relationship. One way of addressing this would be to exogenously impose market exposure—à la John List. A seminal example for this strategy has been provided by a recently published paper by Bryan, Chowdhury, and Mobarak (2014). They randomly assign an incentive to poor households in rural Bangladesh to temporarily out-migrate, and show that out-migration increases consumption at the origin as well as the rates of out-migration even after the incentive is removed. They conclude that out-migration is very profitable and underutilized, and that risk aversion may play a fundamental role in such underutilization. In this paper, we provide complementary evidence based on a non-experimental approach—using an instrument to identify causality. We make use of the low-mobility of farm households with land titles in the West Gojjam area of rural Ethiopia to instrument frequency of market transactions with distance from the nearest daily market.

We find evidence that market exposure is a key determinant of risk preferences of farm households. Specifically, we show that market exposure attenuates risk aversion, and farm households with higher degree of market exposure tend to be less risk averse. Our results are robust to controls for various observable attributes of our farm households, and different sensitivity checks and specifications. Particularly, we address the concern of selective migration thoroughly, and it does not appear to drive our results. The external validity of these results is clearly limited by our use of only landed households, and cannot be verified in our setting. However, the households in our sample account for about 25% of the total households in our study villages, and we have little reason to believe that different dynamics would be at play for landless households, were they identifiable.

Overall, our results indicate that risk preferences evolve in response to market exposure, and suggest that the claim that farm households are inherently risk averse may be excessive. Rather, risk aversion is a trait that can be modified through increasing exposure to markets, and policy can play some role in influencing risk preferences of farm households. This paper thus sheds new light on an alternative mechanism that can potentially link market exposure to economic growth. The penetration of markets in remote areas may be more than a means to better allocate resources. It can be an important channel to reduce risk aversion, thereby reducing the productivity lag of rural households, and helping them to exit the poverty trap.

Finally, one important qualification warrants duly consideration in interpreting our results. While we generally demonstrate that market experience reduces risk aversion, the experimental setting and our data could not allow us to make clear inference about a specific mechanism to explain our findings. Our data are consistent with a number of mechanisms. Specifically, we were not able to neatly distinguish whether the reduction in risk aversion is due to a generally greater appetite for risk or a reduction in loss-aversion. This is an area for future research.

NOTES

1. Risk aversion and loss aversion are technically different concepts. Risk aversion is a general preference for safety and certainty over a variability of an outcome (e.g., yield) and the associated potential for loss (Montier, 2010). Yet, loss aversion is a complex behavioral bias in which people express a tendency to prefer avoiding losses to acquiring equivalent gains

(Kahneman & Tversky, 1979). Meaning, the aggravation that one experiences in losing a sum of money appears to be greater than the pleasure associated with gaining the same amount. A key behavioral consequence of loss aversion in economics and decision theory is that loss averse individuals are risk averse over gains.

2. We return with more detail to the specific case of land tenure in West Gojjam and of our sample in Section 3.
3. This includes communities in which *rist* was not the dominant tenure system, and thus less protected by the provisions of Article 19 over possessing rights.
4. In our dataset we do not separate between *chequn* and *birokrasi*, as the terms have lost common usage.
5. US\$1 was approximately equal to 18.213 Ethiopian Birr during the survey period.
6. While the literature commonly interprets experimental play as reflecting underlying preferences (e.g., [Henrich et al., 2001](#); [Tanaka, Camerer, & Nguyen, 2010](#)), we seek to adopt the simplest risk game used in literature to attenuate the likelihood of capturing other confounding constructs, like expectations, beliefs, and shifts in the constraints of our subjects. For a review and discussion on other common risk games in literature see [Charness, Gneezy, and Imas \(2013\)](#).
7. $E(x) = \frac{1}{2}(2x) - \frac{1}{2}(\frac{1}{2}x) = 0.75x$; $Var(x) = E\{(x - E(x))^2\} = E\{(x - 0.75x)^2\} = 0.0625x^2$.
8. The common practice in the literature is to measure risk loving propensity of individuals by using the proportion of the endowment committed to the risky investment relative to the total endowment. We instead measure the risk aversion. The results would be the same in magnitude but of opposite sign, as the two indices add up to unity.
9. We probe the extent to which the two risk aversion indices capture the same construct, and found a strong but imperfect correlation between them with a coefficient of 0.691 (p -value = 0.001; CI [0.661, 0.722]).
10. Tropical livestock unit is a common unit used to quantify a wide range of various livestock species to a single figure to get the total amount of livestock owned by a household. We employed a tropical livestock unit applicable for SSA.
11. One timad is the land area ploughed by a pair of oxen in a day, and approximately equals 0.25 hectare.
12. The main results remain similar when we use the CRRA instead of the risk aversion index (available on request).
13. The risk aversion index is continuous and censored at zero from below and at one from above, though only one observation is censored at zero. We estimate Tobit models and the results remain similar.
14. The psychology literature has long associated the role of family size in risk behavior with dependency-linked behaviors—large families are expected to have lower dependency-linked behaviors and hence larger tendency to accept more risk than small families (e.g., [Jamieson, 1969](#)).
15. We also present a robustness analysis accounting for alternative interpretation of distance to markets in Section 6 in an effort to eliminate “non-trade” effects of markets on risk preference.
16. Altitude does not enter significantly in our risk aversion model, suggesting that it is a valid instrument.
17. The threshold, 0.25 hectares of land, is effectively less than a quarter of the average household land holding in our sample area. In fact, this provides support to the negative-selection hypothesis of migration that households with strong incentive to out-migrate are those with no or small landholdings ([Chiquiar & Hanson, 2005](#)).
18. As indicated, many of the out-migrants are landless. Accordingly, evaluating all covariates at their means is generous in terms of giving hypothetical households more than they would have if they were actual households.
19. Group discussants stated that households do not move to be located away from market under normal conditions.
20. Some of these households have already resided in the farthest villages to markets in their Kebeles. Their “mobility” may reflect simply movement from one corner to another of the same village. This is not uncommon in Ethiopia where farmers often seek to reside near to their farm plots.
21. We run a simple OLS for our risk aversion model including the mobility dummy and its interaction with distance to markets as explanatory variables but neither enters significantly at conventional levels.
22. We measure rationality of our subjects through a simple experiment based on the Generalized Axiom of Revealed Preference (GARP), which has been shown to be a necessary and sufficient condition for data to be consistent with rational utility maximization ([Varian, 1982](#)). We then employ GARP violations as a nonparametric test to rationality violations. In our design, a GARP violation occurs when a bundle x is chosen when a bundle y is available, where bundle y has at least as much of all goods and strictly more of at least one good than a third bundle z , and z has been directly or indirectly revealed preferred to x .
23. We realize that the tests can only attenuate concerns about unobserved heterogeneity to a large degree but cannot eliminate it completely.

REFERENCES

- Aït-Sahalia, Y., & Lo, A. W. (2000). Nonparametric risk management and implied risk aversion. *Journal of Econometrics*, 94, 9–51.
- Alem, Y., Bezabih, M., Kassie, M., & Zikhali, P. (2010). Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, 41(2), 165–175.
- Ali, D. A., Deininger, K., & Kemper, N. (2015). *Pronatal property rights over land and fertility outcomes: Evidence from a natural experiment in Ethiopia*. Working Paper.
- Barrett, C. (2008). Smallholder market exposure: Concepts and evidence from Eastern and Southern Africa. *Food Policy*, 33(4), 299–317.
- Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Quarterly Journal of Economics*, 112(2), 537–579.
- Becker, G. S., & Mulligan, C. B. (1997). The endogenous determination of time preference. *Quarterly Journal of Economics*, 112(3), 729–758.
- Bedemo, A., Getnet, K., & Kassa, B. (2013). Determinants of labor market exposure choice of farm households in rural Ethiopia: Multinomial logit analysis. *Journal of Economics and Sustainable Development*, 4(1), 133–141.
- Bhattamishra, R., & Barrett, C. B. (2010). Community-based risk management arrangements: A review. *World Development*, 38(7), 923–932.
- Binswanger, H. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics*, 62(3), 395–407.

- Bowles, S. (1998). Endogenous preferences: The cultural consequences of markets and other economic institutions. *Journal of Economic Literature*, 36(1), 75–111.
- Bryan, G., Chowdhury, S., & Mobarak, A. H. (2014). Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica*, 82(5), 671–1748.
- Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and risk preference: Experimental evidence from Afghanistan. *American Economic Review*, 104(1), 123–148.
- Cameron, L., & Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. *Journal of Human Resources*, 50(2), 484–515.
- Cardenas, J. C., & Carpenter, J. P. (2008). Behavioral development economics: Lessons from field labs in developing countries. *Journal of Development Studies*, 44(3), 311–338.
- Cecchi, F., & Bulte, E. (2013). Does market experience promote rational choice? Experimental evidence from rural Ethiopia. *Economic Development and Cultural Change*, 61(2), 407–429.
- Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization*, 87(1), 43–51.
- Chiquiar, Daniel., & Hanson, G. H. (2005). International migration, self-selection, and the distribution of wages: Evidence from Mexico and the United States. *Journal of Political Economy*, 113(2), 239–281.
- Deininger, K., & Jin, S. (2006). Tenure security and land-related investment: Evidence from Ethiopia. *European Economic Review*, 50(5), 1245–1277.
- Delpierre, M., Verheyden, B., & Weynants, S. (2016). Is informal risk-sharing less effective for the poor? Risk externalities and moral hazard in mutual insurance. *Journal of Development Economics*, 118, 282–297.
- Dercon, S. (1996). Risk, crop choice, and savings: Evidence from Tanzania. *Economic Development and Cultural Change*, 44(3), 485–513.
- Dercon, S. (2002). Income risk, coping strategies and safety nets. *The World Bank Research Observer*, 17(2), 141–166.
- Dercon, S. (2008). Fate and fear: Risk and its consequences in Africa. *Journal of African Economies*, 17(Suppl 2), ii97–ii127.
- Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2), 159–173.
- Dohmen, T., Huffman, D., Schupp, J., Falk, A., Sunde, U., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522–550.
- Eckel, C. C., El-Gamal, M. A., & Wilson, R. K. (2009). Risk loving after the storm: A Bayesian-network study of Hurricane Katrina evacuees. *Journal of Economic Behavior & Organization*, 69(2), 110–124.
- Ezra, M., & Kiros, G. E. (2001). Rural out-migration in the drought-prone areas of Ethiopia: A multi-level analysis. *International Migration Research*, 35(3), 749–771.
- Fafchamps, M. (2010). Vulnerability, risk management and agricultural development. *African Journal of Agricultural and Resource Economics*, 5(1), 243–260.
- Falk, A., & Szech, N. (2013). Morals and markets. *Science*, 340, 707–711.
- Fellner, G., & Maciejovsky, B. (2007). Risk attitude and market behavior: Evidence from experimental asset markets. *Journal of Economic Psychology*, 28(3), 338–350.
- Feng, L., & Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets?. *Review of Finance*, 9, 305–351.
- Franken, J. R. V., Pennings, J. M. E., & Garcia, P. (2014). Measuring the effect of risk attitude on marketing behavior. *Agricultural Economics*, 45(5), 1–11.
- Gerber, A. S., & Green, D. P. (2012). *Field experiments: Design, analysis, and interpretation*. New York: W. W. Norton & Company.
- Gneezy, U., Kapteyn, A., & Potters, J. (2003). Evaluation periods and asset prices in a market experiment. *Journal of Finance*, 58(2), 821–838.
- Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112(2), 631–645.
- Gode, D. K., & Sunder, S. (1993). Allocative efficiency of markets with zero-intelligence traders: market as a partial substitute for individual rationality. *Journal of Political Economy*, 101, 119–137.
- Gujarati, D. (2003). *Basic econometrics* (4th ed.) New York, NY: McGraw Hill Inc..
- Haigh, M. S., & List, J. A. (2005). Do professional traders exhibit myopic loss aversion? An experimental analysis. *Journal of Finance*, 60(1), 523–534.
- Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2014). *Do risk preferences change? Evidence from panel data before and after the Great East Japan earthquake*. Unpublished manuscript.
- Harrison, G., Humphrey, S., & Verschoor, A. (2010). Choice under uncertainty: Evidence from Ethiopia, India and Uganda. *Economic Journal*, 120(543), 80–104.
- Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., et al. (2001). In search of homo economicus: Behavioral experiments in 15 small-scale societies. *American Economic Review*, 91(2), 73–78.
- Henrich, J., Ensminger, J., McElreath, R., Barr, A., et al. (2010). Markets, religion, community size, and the evolution of fairness and punishment. *Science*, 327(5972), 1480–1484.
- Humphrey, S., & Verschoor, A. (2004). Decision-making under risk among small farmers in East Uganda. *Journal of African Economies*, 13(1), 44–101.
- Hunnes, D. E. (2012). Understanding rural-to-urban migration in Ethiopia: Driving factors, analytical frameworks, and recommendations. *Journal of Global Health Perspectives*, 1, 1–10.
- Jackwerth, J. C. (2000). Recovering risk aversion from option prices and realized returns. *Review of Financial Studies*, 13(2), 433–451.
- Jamal, K., & Sunder, S. (1996). Bayesian equilibrium in double auctions populated by biased heuristic traders. *Journal of Economic Behavior & Organization*, 31(2), 273–291.
- Jamieson, B. D. (1969). The influences of birth order, family size and sex differences on risk-taking behavior. *British Journal of Social and Clinical Psychology*, 8(1), 1–8.
- Jehle, G. A., & Reny, P. J. (2011). *Advanced microeconomic theory* (3rd ed.) Harlow England: Pearson Education Limited.
- Kabir, M. H., & Shakur, S. (2014). Nonlinear decomposition analysis of risk aversion and stock-holding behaviour of US households. *Applied Financial Economics*, 24(7), 495–503.
- Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1990). Experimental tests of the endowment effect and the coase theorem. *Journal of Political Economy*, 98(6), 1325–1348.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
- Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics*, 129(2), 597–652.
- Kebede, B. (2006). *Land reform, distribution of land and institutions in rural Ethiopia: Analysis of inequality with dirty data*. Working Paper.
- Lamb, R. (2003). Fertilizer use, risk and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics*, 85(2), 359–371.
- Leiva, A. J., & Skees, J. R. (2008). Using irrigation insurance to improve water usage of the Rio Mayo irrigation system in Northwestern Mexico. *World Development*, 36(12), 2663–2678.
- List, J. A. (2003). Does market experience eliminate market anomalies?. *Quarterly Journal of Economics*, 118(1), 41–71.
- List, J. A. (2004). Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica*, 72(2), 615–625.
- List, J. A. (2011). Does market experience eliminate market anomalies? The case of exogenous market experience. *American Economic Review: Papers & Proceedings*, 101(3), 313–317.
- List, J. A., Shaikh, A. M., & Xu, Y. (2016). *Multiple hypothesis testing in experimental economics*. NBER Working Paper 21875.
- List, J. A., & Millimet, D. L. (2008). The market: Catalyst for rationality and filter of irrationality. *BE Journal of Economic Analysis and Policy*, 8(1) 47.
- MacCrimmon, K. R., & Wehrung, D. A. (1990). Characteristics of risk-taking executives. *Management Science*, 36(4), 422–435.
- Maniadis, Z., Tufano, F., & List, J. A. (2014). One swallow doesn't make a summer: new evidence on anchoring effects. *American Economic Review*, 104(1), 277–290.
- Mayhew, B. W., & Vitalis, A. (2014). Myopic loss aversion and market experience. *Journal of Economic Behavior & Organization*, 97, 113–125.
- Mberu, B. U. (2006). Internal migration and household living conditions in Ethiopia. *Demographic Research*, 14(21), 509–540.
- Montier, J. (2010). *Little behavioral book of investing: How not to be your own worst enemy*. New Jersey: John Wiley & Sons.
- Netzer, N. (2009). Evolution of time preferences and attitudes toward risk. *American Economic Review*, 99(3), 937–955.
- Ofcansky, T. P., & Berry L. (1991). *A country study: Ethiopia*. Library of Congress Federal Research Division.

- Pighin, S., Bonini, N., Savadori, L., Hadjichristidis, C., Antonetti, T., & Schena, F. (2012). Decision making under hypoxia: Oxygen depletion increases risk seeking for losses but not for gains. *Judgment and Decision Making*, 7(4), 472–477.
- Rabin, M. (2000). Risk aversion and expected-utility theory: A calibration theorem. *Econometrica*, 68(5), 1281–1292.
- Rabin, M., & Thaler, R. H. (2001). Anomalies: Risk aversion. *Journal of Economic Perspectives*, 15(1), 219–232.
- Rahmato, D. (1984). *Agrarian reform in Ethiopia*. Working Paper.
- Renkow, M., Hallstrom, D. G., & Karanja, D. D. (2004). Rural infrastructure, transactions costs and market exposure in Kenya. *Journal of Development Economics*, 73(1), 349–367.
- Rosenbaum, P. R. (2002). *Observational studies*. New York: Springer.
- Schechter, L. (2007). Risk aversion and expected-utility theory: A calibration exercise. *Journal of Risk and Uncertainty*, 35(1), 67–76.
- Smith, V. L. (1982). Markets as economizers of information: experimental examination of the “Hayek Hypothesis”. *Economic Inquiry*, 20(2), 165–179.
- Staiger, D., & Stock, J. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3), 557–586.
- Tanaka, T., Camerer, C., & Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. *American Economic Review*, 100(1), 557–571.
- Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, 1, 39–60.
- Theil, H. (1971). *Principles of econometrics*. New York, NY: John Wiley & Sons Inc..
- Varian, H. R. (1982). The nonparametric approach to demand analysis. *Econometrica*, 50(4), 945–973.
- Voors, M. J., Nillesen, E. E., Verwimp, P., Bulte, E. H., Lensink, R., & Van Soest, D. P. (2012). Violent conflict and behavior: A field experiment in Burundi. *American Economic Review*, 102(2), 941–964.
- Wik, M., Kebede, T. A., Bergland, O., & Holden, S. T. (2004). On the measurement of risk aversion from experimental data. *Applied Economics*, 36(21), 2443–2451.
- World Bank, 2014. *Risk and opportunity: Managing risk for development*. World Development Report 2014.

APPENDIX A.

Table 9. *Experimental procedure*

Steps in the risk game

1. Each participant is brought to a private location within the premises of the experimental field by an enumerator and assigned an initial endowment of 100 tokens. Each token is worth 0.5 Birr
2. Enumerators explain the rules of the risk game until the respondent is able to convey them back correctly as follows
3. The decision task consists of a choice in which you will decide on a certain amount of your endowment to involve in a risky investment. The investment you make can affect your endowment both negatively and positively. The final pay-out you will earn depends on the choice you make and its outcome during the decision task activities
4. Enumerators present the lottery bag and take out all the balls. The investment is very simple; do you notice the red and white balls? There are eight equal balls. The four balls have white color; the remaining four balls have red color
5. This is how the risk game works. From your endowment, you can decide on any amount between zero and 100 to be used in the risk game, but not more than 100. If you extract a ball with a red color from the lottery bag, the sum you decided to use for this investment will be doubled. But if you extract a ball with a white color, the sum you decided to use for this investment will be halved. In essence, you have $\frac{1}{2}$ chance of doubling the money you decide to use and $\frac{1}{2}$ chance of losing half of it
6. Remember, there is no right or wrong in this game, it's about what you want to do. Then a trial round is performed
7. After the trial round, the respondent is asked to explain the outcome of the 'investment'. If the explanation is correct, the actual game can take place, otherwise the enumerator explains the rules again until the participant understands the game
8. Payments are made after all subjects from the same village complete the game

Table 10. *Estimating risk aversion coefficients using the expected utility framework.*

We employ an expected utility framework to estimate coefficients of relative risk aversion. Let us assume that individuals save a certain amount of their daily income. They may save some of their earnings in a bank account or simply put it in their pocket. This is arguably a reasonable assumption as players do not necessarily consume all of their earnings in one day. A player then chooses optimally how much of his earnings to consume and how much to save for a later date given the interest rate and his discount factor. Let us define the following variables: a player earns a constant daily income of y ; c is the player's consumption; s is his savings; R is one plus the daily interest rate; w is his winnings in the risk game; and β is the discount factor.

The player's problem is then given as:

$$V(w) = \max [U(y + w - s_0) + \beta V(s_0)]$$

and the Euler equation is

$$U'(y + w - s_0) = \beta R U'(y + s_0 R - s_1).$$

Assuming a CES utility function with constant relative risk aversion (CRRA) which is defined as: $U(c) = \frac{c^{1-\gamma}}{1-\gamma}$, we have the following:

$$(y + w - s_0)^{-\gamma} = \beta R (y + s_0 R - s_1)^{-\gamma}, \text{ which implies that } c_t = \phi' c_0, \text{ where } \phi = (\beta R)^{\frac{1}{\gamma}}.$$

We can now solve for the value function:

$$V(w) = \left(\frac{1}{1 - \phi^{(1-\gamma)\beta}} \right) \left(\frac{c_0^{1-\gamma}}{1-\gamma} \right) \quad (4)$$

The intertemporal budget constraint is given by:

$$c_0 = \left(w + \frac{y}{1 - \frac{1}{R}} \right) \left(1 - \frac{\phi}{R} \right) \quad (5)$$

Plugging Eqn. (2) into Eqn. (1) we get our final solution:

$$V(w) = K \left(w + \frac{y}{1 - \frac{1}{R}} \right)^{1-\gamma} \frac{1}{1-\gamma} \quad (6)$$

$$\text{where } K = \left(\frac{1}{1 - \phi^{(1-\gamma)\beta}} \right) \left(1 - \frac{\phi}{R} \right)^{1-\gamma}.$$

Eq. (3) can be used to assess how risk averse players of different income levels must behave in making their choices of each bet or alternatively to estimate risk aversion coefficients after the outcomes of the game play are observed.

Fortunately, the simple structure of our experimental game allows us to further streamline equation (3). Our game is equivalent to the simpler case of a bet on the toss of a coin, and its structure is characterized as: a player decides how much to bet, b , and has a 50/50 chance of winning the high amount hb or the low amount lb where $h > 1 > l > 2 - h$. From equation (3), the player's maximization problem in the context of the setting of our game becomes:

$$\max_b V = \frac{1}{2} K \left((h-1)b + \frac{y}{1 - \frac{1}{R}} \right)^{1-\gamma} \frac{1}{1-\gamma} + \frac{1}{2} K \left((l-1)b + \frac{y}{1 - \frac{1}{R}} \right)^{1-\gamma} \frac{1}{1-\gamma} \quad (7)$$

Solving Eqn. (4) yields the first order condition:

$$b = \left(\frac{y}{1-h} \right) \left[\frac{(1-l)^{\frac{1}{1-\gamma}} - (h-1)^{\frac{1}{1-\gamma}}}{(h-1)^{\frac{1}{1-\gamma}} + (1-l)^{\frac{1}{1-\gamma}}} \right].$$

This characterizes how risk averse players of different income levels must act in making their choices of risky investments (bets). Looking at the equation, we can infer that while R (one plus the interest rate) matters for the determination of the coefficient of relative risk aversion, β (the discount factor) will not (see [Schechter, 2007](#)). Thus, as $R \rightarrow 1^+$ we see $b \rightarrow \infty$ and so, no matter the level of risk aversion, a player should choose to bet the maximal amount. If the player does not, he must be infinitely risk averse. We also calculate the first and second partial derivatives and find that for $R > 1$, $\frac{\partial b}{\partial R} < 0$ and $\frac{\partial^2 b}{\partial R^2} > 0$. This means that for a given bet size, the coefficient of relative risk aversion is increasing at an increasing rate as the interest rate decreases and approaches 1. In fact, as R goes to one from above, $\frac{\partial b}{\partial R}$ goes to $-\infty$.

We employ the optimum of equation (4) to compute CRRA coefficients for our sample. To do so, the different variables in the model are calibrated as follows. First, we assume players will not share their winnings with other members of their family, and define utility only over daily income and winnings from the risk experiment, without including daily income from outside of the experiment options. This is in line with the other studies which estimate risk aversion from experiments in developing countries ignoring income outside the experiment ([Cardenas & Carpenter, 2008](#); [Schechter, 2007](#)). As the players were also working with us on the day of the experiment, this consideration does not seem egregious. Second, we assume that players earn the interest rate given by the Amhara Credit and Saving Institution (ACSI), which is the main lender to small-scale farmers in our study area. This is 5% annually, or 0.01% a day with compounding. One could validly argue that very few of remote rural Ethiopians have access to savings accounts. They may save their money by putting it under their pillow or investing in livestock with much lower returns. As a result, the implied coefficients of relative risk aversion can be interpreted as minimum thresholds for players. Finally, note also that $h = 2$ and $l = 0.5$ in the structure of our game.

Table 11. *Income does not significantly correlate with risk aversion even when market exposure is excluded*

Variables	Risk aversion index (OLS)		
	(a)	(b)	(c)
Male	−0.136*** (0.049)	−0.136*** (0.049)	−0.133*** (0.049)
Age	0.017*** (0.006)	0.018*** (0.006)	0.017*** (0.006)
Age square	−0.0001** (0.0001)	−0.0002*** (0.0001)	−0.0001** (0.0001)
Education	−0.031*** (0.003)	−0.030*** (0.003)	−0.030*** (0.003)
Household size	−0.013*** (0.005)	−0.014*** (0.005)	−0.014*** (0.005)
Land size	−0.004 (0.003)	0.002 (0.003)	−0.003 (0.003)
Livestock	0.0003 (0.002)	0.0003 (0.002)	0.0005 (0.002)
Log per capita income	0.003 (0.010)		
Household income distribution dummy		0.005 (0.023)	0.028 (0.022)
Village total households	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Distance to market (km)	0.003 (0.001)	−8.51e−06 (0.001)	0.002 (0.001)
Market exposure		−0.014*** (0.005)	
Constant	0.488*** (0.160)	0.586*** (0.137)	0.501*** (0.135)
Adjusted R^2	0.38	0.39	0.38
F -test	33.12(1 0, 521)	31.62(1 1, 520)	33.37(1 0, 521)
P -value	0.000	0.000	0.000
N	532	532	532

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; km stands for kilometer; N stands for the number of observations.

Table 12. *PSP estimates as a function of prior probability (π), design power and significant level for our study*

π	PSP
0.01	0.50
0.02	0.67
0.10	0.92
0.20	0.96
0.35	0.98
0.55	0.99
0.65	0.994

Table 13. *Multiple hypothesis testing for multiple outcomes*

Outcome	DI	P -values			
		Multiplicity unadjusted	Multiplicity adjusted		
			List <i>et al.</i>	Bonferroni	Holm
Risk aversion index	0.1386	0.0003***	0.0003***	0.0007***	0.0007***
CRRA	2.3114	0.0003***	0.0003***	0.0007***	0.0003***

Note: DI refers to “difference in means”; *** indicates the corresponding p -values are less than 1%.

Table 14. *Rosenbaum bounds: market exposure effects and unobserved heterogeneity*

Gamma	sig+	sig−	t-hat+	t-hat−	CI+	CI−
1	0	0	0.4422	0.4422	0.4159	0.4696
1.1	0	0	0.4293	0.4559	0.4024	0.4837
1.2	0	0	0.4171	0.4683	0.3905	0.4968
1.3	0	0	0.4059	0.4803	0.3795	0.4086
1.4	0	0	0.3956	0.4911	0.3693	0.5204
1.5	0	0	0.3865	0.5011	0.3596	0.5312
1.6	0	0	0.3777	0.5105	0.3505	0.5417
1.7	0	0	0.3696	0.5201	0.3420	0.5514
1.8	0	0	0.3619	0.5286	0.3340	0.5603
1.9	0	0	0.3542	0.5372	0.3270	0.5690
2	0	0	0.2474	0.5453	0.3203	0.5775
2.1	0	0	0.2408	0.527	0.3137	0.5858
2.2	0	0	0.2345	0.5597	0.3073	0.5937
2.3	0	0	0.2289	0.5667	0.3014	0.6014

Gamma: log odds of differential assignment due to unobserved factors.

Sig+: upper bound significance level (assumption: overestimation of treatment effect).

Sig−: lower bound significance level (assumption: underestimation of treatment effect).

t-hat+ : upper bound Hodges-Lehmann point estimate.

t-hat−: lower bound Hodges-Lehman point estimate.

CI+: upper bound confidence interval ($\alpha = 0.95$ and assumption: overestimation of treatment effect).

CI−: lower bound confidence interval ($\alpha = 0.95$ and assumption: underestimation of treatment effect).

Figure A1. *Kernel density distribution of propensity scores for treated and control farm households.*