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Vienna International Centre, P.O. Box 300, 1400 Vienna, Austria
Tel: (+43-1) 26026-0 · www.unido.org · unido@unido.org

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CENTRE FOR THE STUDY OF AFRICAN ECONOMIES

Department of Economics, University of Oxford

*Managerial Risk Attitudes and Firm Performance in Ghanaian Manufacturing: An Empirical Analysis Based on Experimental Data**

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Prepared by

Måns Söderbom, UNIDO Research Fellow at the CSAE,

in co-authorship with Catherine Pattillo

United Nations Industrial Development Organization
Vienna International Centre
P. O. Box 300
A-1400 Vienna
Austria
Telephone: (43-1) 26026-5231
Fax: (43-1) 26026 6881
E-mail: jestrup@unido.org
Internet: http://www.unido.org

Centre for the Study of African Economies
Department of Economics
University of Oxford
Manor Road Building
Oxford OX1 3UQ
UK
Telephone: +44 (0)1865 271954
Fax: +44 (0)1865 281447
E-mail:
Mans.Soderbom@economics.ox.ac.uk
Internet: http://www.csae.ox.ac.uk/

ABSTRACT

Ghanaian manufacturing firms face a highly risky environment. Firms may attempt to manage these risks by undertaking production, input, and investment strategies designed to lower profit variability. Mean-variance analysis implies, however, that these strategies involve a trade-off with lower expected profits. This paper investigates the extent to which more risk averse managers who face high risks attempt to smooth profits at the expense of lower average profits. We use data from the Ghana Manufacturing Enterprise Survey (GMES) 1994-95, and a specialised component designed to measure managers' risk attitudes using an experimental gambling approach with real monetary payoffs. Joint estimation of profit and profit variance functions which control for unobserved heterogeneity supports model predictions. Firms with more risk averse managers who face high risks have lower profit rate variability and lower mean profit rates. These mean and variance differences are economically important and statistically significant.

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INTRODUCTION

The last decade has witnessed a rapidly growing literature on the effects of risk and uncertainty on firm performance and economic growth. Arguably, this issue is of particular interest for developing countries, where uncertainty often is high and where growth and development typically rely on private sector expansion. A recent macroeconomic contribution by Aizenman and Marion (1999), which is based on data from more than forty developing countries, highlights the adverse affects of risk by documenting a negative correlation between private investment and volatility. One insight from this study is that it is important to adopt a disaggregated approach when analysing the effects of risk. In this paper we adopt a microeconomic perspective and use firm-level panel data from Ghana to examine two aspects of risk, namely what are the correlates of entrepreneurs' risk attitudes; and what are the implications of risk for firm performance, conditional on such risk attitudes. To measure risk attitudes we use data derived from an economic experiment with real monetary payoffs.

As is well known from mean-variance theory, risk averse agents facing high risks will attempt to smooth income at the expense of lower average income. Analogously, a risk averse entrepreneur will seek to smooth the firm's profit streams, for example by making conservative production or input choices, diversifying economic activities, or investing in flexible inputs and types of capital. In this way the firm attempts to protect itself from adverse profit shocks before they occur. Because of mean-variance trade-offs, however, the benefits to risk-averse producers in terms of lower profit variance come at an opportunity cost, as expected profits typically must be sacrificed for lower risk. Furthermore, following from insights in the agricultural household literature, profit smoothing will be more likely to occur when firms anticipate being unable to borrow or insure. Since credit and insurance markets in Africa tend to be weak, one can expect that profit smoothing may be particularly prevalent in African firms. This implies that the costs of risks will be high in Africa and that African firms present interesting cases to study these mechanisms.

Another reason for the interest in exploring the effects of risk aversion on firm performance stems from the controversy surrounding the relationship between investment and uncertainty. For a risk-neutral, competitive firm, higher uncertainty increases investment, as long as the marginal product of capital is a convex function of the random variable. As this result seems paradoxical and inconsistent with reality, models of irreversible investment under uncertainty introduce an element of concavity, or asymmetry that lead to the opposite conclusion. Note that these models assume that firms are risk-neutral. In addition to irreversibility, however, it could also be that risk aversion plays a role. For example, Nakamura (1999) shows theoretically that risk aversion is another mechanism that invalidates the convexity of the marginal product of capital and leads to a negative relationship between investment and uncertainty.

In addition, Teal (1998) has shown that although the real value-added of the Ghanaian firms in this dataset grew significantly during 1991-95, there was no contribution to growth from technical progress. Another longer-run potential cost for risk-averse firms choosing safe, low risk, lower return portfolios of activities is a reluctance to adopt newer, riskier technologies. This behaviour may be contributing to a less dynamic and less sustainable growth process for the Ghanaian manufacturing sector.

We explore the effects of risk aversion and demand uncertainty on the level and the variance of profit rates. A puzzling finding for a panel of African firms, including firms from Ghana, is that rates of return on capital (both median and marginal) are relatively high, while investment levels are quite low. (Bigsten et al. 1999b; Gunning and Mengistae, 1999). The explanation that has been proposed is that this situation reflects the high risks and uncertainties facing African firms. However, if managers are risk averse, this may contribute to a reluctance to invest even given relatively high profit rates. It may also be that managers require even higher rates of return, attainable only if they were doing less profit-smoothing.

In this paper we measure managers' risk attitudes using data from an experimental gambling approach with real payoffs that was added as a component to an ongoing panel survey of Ghanaian manufacturing firms. The first step in our empirical analysis is to examine whether these firm specific risk aversion measures are correlated with firm and managerial characteristics. Next we develop an empirical model in which the profit rate and variance are jointly estimated, and investigate whether managers facing high risks and with high risk aversion trade-off lower profits for more stable ones. One important feature of this model is its ability to control for unobserved heterogeneity in a flexible manner.

The paper is structured as follows. Section 2 discusses the underlying theoretical framework, while Section 3 describes the data and descriptive statistics, including details on the experiments measuring risk attitudes. Section 4 first empirically models the determinants of risk aversion, and then estimates profit and variance functions, controlling for unobserved heterogeneity. Section 5 summarises and draws conclusions.

II. Theoretical Framework

African firms face a highly risky environment. Risks stem from, for example, uncertainty about demand, price and exchange rate volatility, difficulties in contract enforcement, and unreliable infrastructure, notably electricity. Following Alderman and Paxson (1992), we can distinguish between two broad classes of strategies by which agents can mitigate the consequences of risk. The first stage is *risk management*, where in the absence of perfect insurance markets, households or firms undertake actions to reduce ex ante income variability. Ex post, after income is realised, households or firm managers employ *risk coping* strategies that smooth consumption intertemporally by savings and across units though risk-sharing arrangements.

A few recent papers have focused on the responses of African firms to the types of risks noted above. Fafchamps et al. (2000) show that Zimbabwean firms hold higher liquid assets and inventories in response to high levels of contractual risk. Using a multi-African country data set, Bigsten et al. (1999c) report results indicating that workers help their employers to smooth profits by accepting more variable wages in return for a wage premium, a strategy of sharing risks within the firm. Both of these studies provide evidence of risk management by firms. One risk coping mechanism that has been studied is Ghanaian firms' sharing of risks in business networks by accepting late payment and building in other contract flexibilities to account for excusable breaches due to unforeseen shocks (Fafchamps, 1996). However, while evidence is accumulating on the mechanisms through which African firms manage and cope with risk (e.g. by inventory adjustment, offering a wage premium, or by forming networks), there has been no direct exploration of the primary implication of risk management. Here we test directly the extent to which managers facing high risks and with high levels of risk aversion trade-off lower profits for less variable ones.

Several agricultural household studies have analysed, theoretically or empirically, the mean-variance trade-off for income (Dercon, 1996; Morduch, 1994; Adam and O'Connell, 1998). Under the assumption that households allocate labour between a risky, high-return activity and a safer, lower-return one, these studies have shown how the share devoted to the safer activity is increasing in the relative riskiness of the second activity, and in the household's degree of risk aversion. Further, if risk aversion is decreasing in wealth, higher wealth lowers the allocation to the safer activity.

The parallel issue for firms has been less explored. Rosenzweig and Binswanger (1993; henceforth RB), however, develop a framework in which entrepreneurs maximise expected utility derived from the profit streams of the firms, where expected utility is dependent on the first two moments of consumption. In particular, RB assume that the manager chooses a "portfolio" of activities, or types of capital inputs, which together with a productivity shock influence the mean and variability of profits. The extent to which variation in profits feeds into variation in consumption depends on the entrepreneur's ability to engage in borrowing or lending, or to buy or sell personal durable assets to smooth consumption, reflected in wealth. From the first order conditions of the problem it can be shown that for each production activity, there must be a positive association between its marginal contribution to mean profitability and to profit variability.[1] Hence, when an entrepreneur shifts resources to the more risky production activity, it induces a rise in average profitability.

There are several possible reasons why the mechanisms discussed by RB may be relevant for our sample of Ghanaian manufacturing firms, hence possibly leading to mean-variance trade-offs in profits.[2] We will list some here. Firstly, the firm could choose to produce a line of lower-return, standardised products, with set prices, rather than venturing into more customised, differentiated products. While the latter types of products have potentially higher return, there is more uncertainty about customer demand and selling prices. Secondly, the production process could be organised to use inputs that provide greater flexibility to respond to shocks, but may generate lower returns. Greater use of casual workers may be one example. Thirdly, the firm could invest in some assets that have higher but more risky returns stemming from, say, the uncertainty of power supply. This may apply to the outcomes of employing electric sewing machines versus foot-pedalled ones in the garment sector, or oil or electric powered saws versus hand-saws in the wood products firms, for example. Fourthly, the firm could engage in greater horizontal or vertical diversification. In diversifying, a firm is likely to lose possible gains from economies of scale and accept lower returns while gaining in terms of risk reduction.[3] A final example relates to the choice of intermediate inputs. While some inputs may be generally of lower quality, and thus lead to lower average profitability, their delivery at the time promised may be more certain, lowering profit variability. The case of some types of domestic versus imported inputs may be relevant.

In Section 4 we empirically explore three of the implications of the RB model. The first is that in a context where uncertainty is not perfectly insurable, more risk-averse entrepreneurs will choose activities that lead to lower profit variance and lower average profits per unit of capital. To test this we are fortunate to have some direct information on managers' risk attitudes, obtained from an experimental gamble with real payoffs. The second hypothesis that we will test is that greater uncertainty, due to a higher standard deviation of exogenous shocks, results in shifting more to the safer activity, such that average profitability and profit variability are reduced. To this end, we use unusually detailed data on managers' demand expectations about to create a measure of subjective uncertainty. The third theoretical implication is that, if wealth facilitates ex post consumption smoothing and if relative risk aversion is decreasing in wealth, managers without large (fixed or liquid) assets will be more willing to sacrifice income for less variability.[4] In the empirical analysis we are somewhat limited in our ability to test the latter implication because there is little information in the data set on managers' wealth or opportunities for ex post consumption smoothing. However, we include measures of the potential for selling personal durable assets as a proxy for these opportunities.

III. DATA AND DESCRIPTIVE STATISTICS

The Ghanaian Manufacturing Enterprise Survey (GMES) has collected panel data for the five-year period 1991-95 for a sample of approximately 200 manufacturing firms.[5] The surveyed firms are located in the four main cities of Accra (the capital), Cape Coast, Kumasi, and Takoradi, and represent four industrial sectors, namely food and bakery, wood and furniture, textiles and garments, and metalworking and machinery. The lottery and expectations data were only collected in the 1994-95 survey, and only for small and medium sized firms, and we will therefore focus on a sub-sample of the full dataset covering the 1994-95 period for 78 firms. All these firms are privately owned. In terms of employment, the largest of these employ 160 people, and the smallest has one employee. For details on the sample selection and variable definitions, see the Appendix. Sample statistics are shown in Table 1.

Table 1 contains sample statistics of two profit measures which we will look further into in the econometric analysis below, the profit to output ratio and the profit to capital ratio. One distinguished feature of both measures is that the median is smaller than the mean, suggesting that the distribution of profit rates is skewed to the right. Indeed, when observations are pooled the estimated sample skewness is equal to 2.17 for the profit to output ratio and 2.48 for and the profit to capital ratio. For the profit to output ratio, the high skewness number is largely generated by four observations with extremely high profit rates. When these are eliminated from the sample, the skewness number decreases to 0.68. Further, it is clear that the average return to capital is strikingly high, usually larger than 100%. This is a feature of African manufacturing firms that has been documented in the literature (Bigsten et al., 1999a). Bigsten et al. suggest that this situation reflects the high risks and uncertainties facing the firms. As a first step towards examining the extent to which there are mean-variance trade-offs in profits, we computed firm specific means and standard deviations of profits, and calculated their correlation.[6] The correlelation is 0.58 for the profit to output ratio and 0.66 for the profit to capital ratio. Both estimates are significantly different from zero at the 1% level of significance. Positive correlation between the mean and the standard deviation is consistent with the mechanisms discussed in Section 2.

One unusual feature of the GMES 1994-95 data set is that it contains experimental data on managerial risk aversion. Following Binswanger (1980), these data were obtained by asking respondents to choose between seven lotteries with varying expected return and variance, where higher return can only be obtained by accepting higher variance. Table 2 shows the details of the experiment. Once the respondents chose a lottery, a coin was tossed and they received the outcome indicated by heads and tails in the table. Hence, an individual who chose Lottery 1 simply got 1,000 Cedis regardless of the outcome of the coin toss; someone choosing Lottery 2 got 900 Cedis on heads and 1,900 Cedis on tails, and so on. Lottery 7 is the high-risk, high-return alternative where the respondent would get nothing on heads and 4,000 on tails. Given the design of the experiment we can compute two measures of risk preferences. First, we calculate intervals for the coefficient of relative risk aversion, denoted *S*, assuming the underlying utility function to be $U(x) = (x^{1-S} - 1)/(1-S)$. Second, we compute intervals for the "slope", denoted *Z*, of the trade-off between expected return and standard deviation. These measures are shown in the right part of Table 2.

The game was first played without giving the actual payoffs (hypothetical), and then for real money. Figure 1 shows the distribution of lottery choices, based on the gamble with real payoffs.[7] Clearly there is substantial variation in the data. Twenty-one percent of the managers chose the risk-free alternative giving a certain outcome of 1,000 Cedis. Lotteries 2-4 each attracted between 15% and 20% of the respondents, whereas Lotteries 5 and 6 were less popular. The most risky lottery (Lottery 7) was chosen by 18% of the respondents. Hence, our sample contains individuals who appear to be very risk averse, and others who are quite willing to take risks. In Section 4 we will explore if this variation in risk attitudes maps into variation in profitability, according to the prediction of our theoretical framework.

We maintain that the lottery experiment is a good method for eliciting information on managers risk preferences. Another alternative for measuring risk attitudes that has been tried is interviews that pose choices between hypothetical but realistic production alternatives, geared to finding certainty equivalents of risky prospects. Binswanger (1980) shows that this method is subject to interviewer bias and unstable results when individuals are resurveyed. In more recent literature, risk aversion parameters have been estimated as part of often complex structural models. There still appears to be some advantage to the lottery experiments, however, since the method is more direct and does not rely on model or estimation assumptions.

Two key aspects of the lottery design are that participants receive actual monetary payoffs, and that the payoff size is large relative to average incomes. One frequent objection to these types of experiments is that the lottery's ability to measure risk attitudes is compromised because it does not subject the individual to actual losses.[8] In response, Binswanger (1981) has argued that opportunity losses are theoretically equivalent to real losses in utility-based models. In addition, the rural India experiment also tested giving the participants money some days before, so that when they played the lottery game they put these funds at risk, and found no statistical differences in choices. The conclusion was that participants treated opportunity losses much like real losses.

Another unusual element of the GMES dataset is that fairly detailed data on managers' expectations were obtained. Managers were asked about their one-year and three-year ahead expectations of demand for their firms' products. However, rather than only asking for point estimates, i.e. what percentage change they expected, firms were asked to assign probabilities to a range of potential percentage changes in demand, so that the probabilities summed to 100. The categories used were as follows: decrease by more than 30%; decrease by 20 to 30%; decrease by 10 to 20%; decrease by 0 to 10%; no change; increase by 0 to 10%; increase by 10 to 20%; increase by 20 to 30%; increase by more than 30%. Hence, a manager believing that there was an equal likelihood that demand would either increase by 0-10%, by 10-20%, or by 20-30%, would put probabilities of 33.3 in each of these intervals. Pattillo (1998) has used these data in analysing investment behaviour, and here we will use them to analyse profits, in terms of levels and variance. Focussing on managerial uncertainty, we compute each manager's one-year ahead subjective variance of expected demand growth (see Appendix for details on how these calculations). The frequency distribution of this variable is shown in Table 3. Most managers appear to be relatively certain about one-year ahead demand, as 55% of them have a subjective variance less than 10%. Some firms however have very high variances, sometimes ranging over 50%.

IV. Econometric Analysis

Before turning to the analysis of the consequences of risk aversion, we examine how firm and managerial characteristics are correlated with risk aversion. This is an issue which has not been subject to much empirical analysis in the literature. Binswanger (1980) surveyed Indian farmers using an experimental gamble approach similar to that described above. Based on the lottery selections made by the respondents, Binswanger computed point estimates of partial risk aversion coefficients and regressed these (in logarithms) on various personal characteristics such as gender, occupation, age, income, financial and non-financial assets, and schooling. Coefficient estimates from six models were reported, and the results were somewhat mixed with coefficients not always being significant. Nevertheless, to summarise the main results, risk aversion was found to be negatively associated with wealth, assets, schooling (proxying "human wealth"), and positively related to age (except possibly for games at high stakes). More recently, Donkers and van Soest (1999) have analysed how a subjective and non-experimental measure of risk aversion from a Dutch household survey is related to household characteristics. They find that women are more risk averse than men, and that risk aversion is increasing in age and in one of their two cross-sections, somewhat surprisingly, in income, which is a proxy for wealth.

Determinants of Risk Aversion

To analyse the determinants of risk aversion we first need to decide how to treat the dependent variable. Since the lotteries are ordered from the least to the most risky gamble, we will use an ordered probit. To avoid having too many parameters we have grouped the seven lottery choices (see Table 2 and Figure 1) into three risk aversion categories: "high risk aversion", if the respondent chose Lottery 1 or 2; "intermediate risk aversion", if the respondent chose Lottery 3 or 4; and "low risk aversion", if the respondent chose Lottery 5, 6 or 7. All regression results reported in this paper follow this grouping, although every regression also has been estimated without grouping. The latter results, which are available on request, were similar and provided the basis for the grouping principle just described. The ordered probit model can be written

(1) $RA_i^* = \theta' w_i + \nu_i$,

where we observe risk aversion category:

$$\begin{aligned} RA_i &= 1 \quad \text{if } RA_i^* \le 0 && \text{(high risk aversion);} \\ &= 2 \quad \text{if } 0 < RA_i^* \le \tau_1 && \text{(intermediate risk aversion);} \\ &= 3 \quad \text{if } RA_i^* > \tau_1 && \text{(low risk aversion),} \end{aligned}$$

and where w is a vector of explanatory variables, ν is a normally distributed residual, and τ_1 is a threshold parameter to be estimated jointly with the parameter vector θ. Drawing on the modelling strategy of Binswanger (1980), we hypothesise that age, education, and assets are determinants of risk aversion, basically because they are proxy variables for physical and human wealth. Wealth, in turn, is expected to be positively correlated with willingness to accept risk. Further, we include working experience as another proxy for human wealth, and a parental background dummy for whether or not the main occupation of the respondent's father was running a business. The idea behind the latter variable is that parental entrepreneurship might be beneficial for both physical and human wealth, for instance by providing managerial know-how. Further, since running a business typically is associated with a higher risk than being an employee, parental entrepreneurship can be expected to be correlated with willingness to accept risk if risk attitudes are correlated between parents and their children. Unfortunately, there are no data on managerial assets, but since the manager is also the owner in almost all firms in the sample, we use the replacement value of the firm's capital stock as a proxy. Finally, we add control variables for industry, location, and firm status.[9]

Ordered probit results are reported in Table 4. Due to missing data on one or several of the explanatory variables, the results are based on a sample of 67 firms (sample means and standard deviations are reported below the table). The capital stock is insignificant, but the coefficients on working experience, education, age of the manager, and father had business are all significant at the 10% level or lower.[10] We find that the probability that a risky lottery will be selected depends positively on experience, education, and parental entrepreneurship, and negatively on age. Hence, an individual who is well educated, young, has some working experience in the current industry, and whose father's main occupation was running a business will typically choose a risky and high-return lottery. Conversely, an individual with the opposite characteristics will typically choose a safe, low-return lottery. This seems intuitively plausible and it also squares well with the results reported by Binswanger. We tentatively conclude, therefore, that the gambling data contain valuable information on managers' risk attitudes.

Consequences of Risk for Profits

In order to analyse the mechanisms discussed in Section 2, we will estimate profit regressions using the data described above on risk attitudes and uncertainty as explanatory variables. Our empirical models will be of the form:

$$(2) \qquad y_{it} = h(\beta' x_{it}, \gamma_1 \mu_i) + \varepsilon_{it},$$

where y is the dependent variable, $h(.)$ is a function, β is a parameter vector associated with the vector of explanatory variables x, μ is a firm-specific random effect with mean $\bar{\mu}$ and variance σ_{μ}^2, γ_1 is a factor loading, and ε is a residual. We interpret the residual as an unanticipated shock to profits, stemming from underlying uncertainty of the kind discussed in Section 2. Because the firm manager can choose between a number of activities with different degrees of risk, he/she will effectively have some control over the variance of ε. As a result, the residual will be heteroskedastic; for instance, highly risk averse managers will typically choose activities with low risk, and the variance of ε will therefore be low for such firms. Hence it is important for our purposes to allow for a rich heteroskedasticity structure. Assuming that ε follows a normal distribution, we specify the variance as:

$$(3) \qquad \sigma_{it}^2 = \sigma^2 \exp(z_{it}' \alpha + \gamma_2 \mu_i),$$

where σ^2 is a constant, z is a vector of explanatory variables, α is a vector of parameters, and γ_2 is a factor loading.[11] This structure takes a very flexible stance, allowing the variance of ε to depend both on observed and unobserved heterogeneity.

One important feature in equations (2)-(3) is the control for unobserved heterogeneity, through the random effect μ.[12] In order to integrate μ out the of the likelihood function we will use a nonparametric approach suggested by Heckman and Singer (1984), where we take μ to follow a discrete multinomial distribution with M points of support, $(\mu_1,...,\mu_M)$, with the associated probabilities denoted PI_m. This approach, known as a discrete factor approximation, is flexible in that arbitrary distributional assumptions regarding the distribution of μ are avoided, while at the same time it is relatively efficient compared to multiple-stage estimation procedures. In an extensive Monte Carlo study, Mroz (1999) reported results indicating that estimators using discrete factor approximations compare favourably to maximum likelihood estimators correctly assuming the distribution of μ to be normal, and that they perform much better than maximum likelihood estimators incorrectly assuming normality.[13] The likelihood function is given in the appendix.

Empirical Models and Results

To analyse the implications of managerial risk attitudes and uncertainty for profits we will run profit regressions of two kinds. The first does not follow from the firm's profit maximisation problem while the second does. We begin by looking at the profit to output ratio, which essentially measures the degree to which the firm manages to generate surplus liquidity once operating costs have been covered. To the extent that the "portfolio" choice of activities affects profits, as predicted by theory, this will affect the profit to output ratio as well. Although not derivable from the firm's maximisation problem, we believe that a regression of the profit to output ratio on a set of explanatory variables will be useful as a benchmark to which the second, more theoretically appropriate model, can be compared. In the second model the profit to capital ratio is the dependent variable. As shown in Section 3, this variable exhibits considerable skewness which may cause problems in estimation in the sense that the observations at the far end of the tail may heavily influence the regression results. Further, it does not seem unlikely that this skewness in fact is generated, at least to some degree, by measurement errors in the capital stock.[14] The profit to output ratio is less skewed and it is likely to be less sensitive to measurement errors since it is a flow-flow variable, rather than flow-stock.

The theory discussed in Section 2 predicts that the inter-firm variation in managerial uncertainty and risk attitudes, documented in Section 3, will map into inter-firm variation in the composition of activities, with mean-variance effects on profits. In the empirical analysis that follows, we will use the subjective variance to represent managerial uncertainty, and the lottery choices to proxy risk aversion. Another implication of theory concerns wealth effects. If wealth facilitates ex post consumption smoothing or if relative risk aversion is declining in wealth, then the RB model outlined in Section 2 predicts that an increase in managerial wealth will be associated with a portfolio shift into high-risk and high-return activities. Although the data on managerial wealth are scanty as touched upon above, we do have information on whether or not the manager owns a house and a motor vehicle. We will use these to proxy wealth.

In our first model we take the profit to output ratio to be a linear function of the manager's subjective variance, V_i^E, the risk aversion categories RA_k, k = 1,…,3, with the riskiest selection RA_3 as the omitted category, and the dummy variables for house and motor vehicle ownership, denoted *HO* and *MO*, respectively. We add the capital stock (measured in logarithms), *k*, partly to proxy wealth effects and partly to control for firm size, along with control variables for industry, firm status, firm age, location, and time.[15] Adding finally the unobserved firm effect μ and the residual, the reduced-form specification can be written[16]

$$(4) \qquad \left(\frac{\pi}{y}\right)_{it} = \beta_0 + \beta_1 k_{it} + \beta_3 V_i^E + \beta_4 HO_{it} + \beta_5 MO_{it} + \sum_{k=1}^{2} \lambda_k RA_{ik} + controls_{it}^{\pi} + \mu_i + \varepsilon_{it} .$$

We choose a similar set of variables for the variance function, the only difference being the number of control variables:

$$(5) \qquad \sigma_{it}^2 = \sigma^2 \exp\left(\alpha_1 k_{it} + \alpha_2 V_i^E + \alpha_3 HO_{it} + \alpha_4 MO_{it} + \sum_{k=1}^{2} \phi_k RA_{ik} + controls_{it}^{\sigma} + \gamma_2 \mu_i \right).$$

Regression results, based on three support points for the random effect, are shown in Table 5.[17] In Column (a) we have estimated the model without including the risk aversion variables, in order to provide a benchmark. In the profit equation we see that our proxy variables for wealth, i.e. the capital stock, and the dummy variables for owning a house and a motor vehicle, have positive coefficients, where those on capital and motor vehicle are significantly different from zero at the 10% level or lower. This squares with the theoretical implications, as discussed above. Further, managerial uncertainty, as measured by subjective variance, has a negative and highly significant effect on profits, consistent with the prediction that increasing uncertainty generates a shift to less profitable activities.

In the variance equation we obtain a positive and significant (at the 5% level) coefficient on owns motor vehicle, whereas the estimated coefficients on owns house and the capital stock are insignificant.

Subjective variance is highly significant and enters with a negative sign, consistent with the notion that the firm will attempt to reduce portfolio variability when uncertainty increases. Finally, the unobserved heterogeneity estimates strongly indicate that heterogeneity is present, and that there is a positive correlation between unobserved factors affecting variance and factors affecting profits. This too is consistent with the risk aversion framework for reasons discussed above.

We now turn to the second version of the profit to output regression, which includes the risk aversion variables as regressors (as measured by the lottery data, where the grouping is as described in Section 4.1). Since the least risk averse category is the omitted dummy, we would expect the coefficients on the two lottery categories to be negative, with the coefficient on high risk aversion being smaller (i.e. larger, in absolute terms) than that on intermediate risk aversion. Regression results, reported in Column (b), strongly support theory in the sense that managers choosing the conservative gambles have lower profits and lower variance in the shocks to profit than less risk averse managers. The risk aversion coefficients are negative and highly significant in both equations. In the profit equation the coefficient on high risk aversion is larger than that on intermediate risk aversion, which is strictly not consistent with theory.[18] In the variance equation, however, the ordering is more in line with expectations.

As in Column (a), the estimated capital stock coefficient in the profit equation is positive and significant, whereas it is insignificant in the variance equation. Further, as in the previous regression, in both equations, owning a motor vehicle enters with positive and significant coefficients, and subjective variance enters with negative and significant coefficients. Neither of the coefficients on owning a house is significant. Finally, it again appears important to control for unobserved heterogeneity, since the estimated θ and the support point probabilities are highly significant. In contrast to the model in Column (a), however, the factor loading γ_2 is insignificant, suggesting that unobserved heterogeneity might be negligible in the variance equation, once we have controlled for risk aversion.

The next step is to examine how the above results compare to a model based on a theoretically more appropriate framework. Our second model is derived from the firm's instantaneous profit maximisation problem:

(6) $$\pi(p,w) = \max_{L} pAF(L,K) - wL,$$

where p is the (exogenous) output price, A is efficiency, w is the (exogenous) wage, $F(.)$ is a production function, L is labour which is assumed perfectly flexible, and K is capital, assumed quasi-fixed. For simplicity, we assume that the production function is Cobb-Douglas with constant-returns to scale, which means that we can use the first-order condition for L and rewrite (6) as :

$$(7) \qquad \frac{\pi(p,w)}{K} = \alpha^{\alpha/(1-\alpha)}(pA)^{\alpha/(1-\alpha)} w^{\alpha/(\alpha-1)},$$

where α is the labour elasticity in the production function.[19] We proxy variation in prices and efficiency across firms by the same control variables as above, and by the unobserved firm effect μ, and we control for temporal variation by using a year dummy. Further, we adjust (7) to allow for dependence on subjective variance and risk aversion. If all firms were risk neutral, these variables would be irrelevant and the associated coefficients would be insignificant. Finally, since firms occasionally make losses we assume the residual to be additive, with all the properties discussed above. Since the residual has mean zero this means that firms will have non-negative expected profits, yet actual profits may be negative due to a bad shock. With these adjustments of the theoretical equation, we write the empirical profit function as:

$$(8) \qquad \left(\frac{\pi}{K}\right)_{it} = \exp\left(\beta_0 + \beta_1 HO_{it} + \beta_2 MO_{it} + \sum_{k=1}^{2} \lambda_k RA_{ik} + controls_{it}^{\pi} + \mu_i\right) \cdot \left(V_t^E\right)^{\beta_3} w_{it}^{\beta_4} + \varepsilon_{it} ,$$

and we specify the variance function as:

$$(9) \qquad \sigma_{it}^2 = \sigma^2 \exp\left(\alpha_1 HO_{it} + \alpha_2 MO_{it} + \sum_{k=1}^{2} \phi_k RA_{ik} + controls_{it}^{\sigma} + \gamma_2 \mu_i\right) \cdot \left(V_i^E\right)^{\alpha_3} L_{it}^{\alpha_4} .$$

One notable difference between equation (9) and (5) is that employment enters as an explanatory variable. The reason is that when modelling the profit to capital rate, we believe that it is important to condition the variance on firm size as it is likely that small firms have higher variation in their profit rates than larger firms.

Table 6 reports the regression results, based on five support points for the random effect, for the profit to capital ratio model. Again we begin in Column (a) without the risk aversion dummies. In the profit equation the coefficient on subjective variance is negative, as expected, and just fails to be significant at the 10% level (the p-value is equal to 0.1006). Further, we note that the wage coefficient is negative in the profit equation as expected, but not significantly different from zero. The coefficients on owns house and owns motor vehicle are both insignificant.

In the variance equation, owns house enters highly significantly but with the “wrong” sign (negative), whereas the coefficient on owns motor vehicle is positive and significant at the 10% level. The estimated coefficient on subjective variance is negative, as expected, and significant at the 10% level. Somewhat surprisingly there is no significant size effect in the variance equation. One reason might be that our controls for unobserved heterogeneity are sufficient to control for such mechanisms.[20] As in the regressions reported in Table 5, there is strong support for the presence of unobserved heterogeneity in the data. In fact, the log likelihood value of the model in Column (a) exceeds the log likelihood value of the model without unobserved heterogeneity by 126, which is clearly a considerable improvement given that only 10 additional parameters have been introduced in the heterogeneity model. As before, the factor loading in the variance equation is positive, indicating a positive correlation between the unobserved factors affecting profits and those affecting variance.

In Column (b) we add the risk aversion variables to both equations in Column (a). Clearly, the addition of these variables has substantial effects. Many of the coefficient estimates change quite dramatically, and the log likelihood value increases by 13.5 which is a large improvement given that there are only 4 new parameters. In the profit equation, owns house is now negative and significant, which runs counter to what we were expecting, whereas owns motor vehicle is positive and close to being significant at the 10% level (the p-value is equal to 0.104). Further, we obtain negative and highly significant (at the 1% level) coefficients on subjective variance and the risk aversion dummies. Hence, uncertainty seems to reduce profits, and firms which are run by risk averse managers appear to have lower profit rates than firms whose managers choose high-return and high-risk lotteries (the omitted category).[21] The estimated wage coefficient is still insignificant.[22] In the variance equation, we see that the coefficient on owns house still is negative, but now insignificant, whereas owns motor vehicle is positive and significant at the 1% level. As before, subjective variance is negative and highly significant, and so are the risk aversion dummies.

Specification Tests

Turning finally to model specification issues, we focus on three questions. Firstly, given the correlation between managerial background variables and risk attitudes documented in Table 4 (the ordered probit), can we be reasonably confident that the significant risk attitude effects obtained in Table 6 (Column b) are not in fact driven by the omission of the background variables? We note that for the model in Column (a) there is strong support for omitted variable bias, as indicated by the reported Wald test.[23] However, this result may very well be due to the omission of the risk aversion variables. When the risk aversion variables enter the model (Column b), the test statistic for omitted variables shrinks dramatically, implying that we cannot reject the hypothesis that there are no omitted variables, at conventional levels of significance.

Secondly, can we be reasonably confident that the risk attitude effects are not biased by endogeneity? This would be the case, for instance, if unobservable factors affecting risk attitudes were correlated with the unobservable factors affecting the level and variance of profits. To test for this we amended the random effect μ multiplied by an additional factor loading γ_3 to the ordered probit specification in Table 4, and then estimated the probit jointly with the profit function in Column (b). A non-zero γ_3 would then indicate presence of endogeneity of the kind just discussed. However, we cannot reject the hypothesis that γ_3 is zero, as indicated by the very low *z*-value reported in Table 6. This suggests endogeneity not to be a problem here.

Thirdly, and finally, how well does our preferred model manage to replicate the sample data? In Figure 1 we show diagnostic plots, based on the results in Table 6, Column (b). Clearly, our model does a fairly good job in capturing the heavily skewed sample distribution of the profit rate. This relative success is to a large degree due to the nonparametric unobserved heterogeneity approach. When plotting actual versus fitted profit rates (Panel c in the figure), most of the points lie quite close to a 45 degree line (not drawn).[24] As expected, the largest residuals occur at large actual profit rates. A related issue concerns the assumption of the residuals being normally distributed, made in Section 4. Panel (d) shows the density of the standardised residuals. Judging from the plot, normality does not seem to be a very strong assumption. Indeed, when formally tested, normality cannot be rejected at conventional levels of significance.[25]

Based on the results in Tables 5 and 6, we conclude that variation in managerial uncertainty and risk attitudes will have economically important effects on the level and variance of profits. Focussing on the results in Table 6, Column (b), the coefficient on high risk aversion implies that a firm with a manager in this category will have an expected profit rate equal to exp(-0.59)=55% of the expected profit rate in a firm associated with one of the riskiest gambles. The corresponding number for intermediate risk aversion is exp(-1.39)=25%. Are these figures not too substantial to be realistic? We know from Section 2, and from other studies (e.g. Pattillo, 1998; Bigsten et al., 1999a), that there is considerable inter-firm variation in profit to capital ratios in African manufacturing. Therefore it does not seem unreasonable that explanatory variables may turn out to have quite pronounced quantitative effects. Further, it does not appear that these results are driven by the functional form of our model.[26] Next, in the variance equation, the coefficient on high risk aversion implies that a firm belonging to this category will have a standard deviation in shocks to profit around 35% of the standard deviation for the least risk averse firms.[27] The corresponding number for intermediate risk aversion is 18%. Again, these are substantial magnitudes. The subjective variance term finally, has a coefficient equal to -0.32 in the profit equation and -0.84 in the variance equation. These estimates are readily interpretable as elasticities: a doubling in subjective variance, for instance, will reduce expected profits by approximately $1\text{-}2^{-0.32}$ = 20% and the variance of shocks by $1\text{-}2^{-0.84}$ = 44%.

V. Summary and Conclusions

Ghanaian manufacturing firms operate in an environment characterised by high and, at least partially, uninsurable economic risk. As a consequence do firms trade-off lower for more stable profits -- the fundamental risk management strategy? In particular, can we find support for the prediction that inter-firm variation in managerial risk attitudes and in uncertainty will map into inter-firm variation in the composition of activities, with mean-variance effects on profits? We have empirically examined these issues using the GMES panel data set, which contains extensive information on firm and managerial characteristics as well as data on managers' risk attitudes and their subjective expected variance of demand. Our empirical method has two important strengths. First, consistent with the theoretical hypothesis, we estimate profit and profit variance functions jointly. Thus, the model is fitted such that the impact of managers' risk attitudes and uncertainty (in addition to the other variables) on the mean and variance of profits is determined simultaneously. Second, we use a flexible, non-parametric approach to account for unobserved firm heterogeneity. It is important to employ a rich heteroskedasticity structure, so that we do not attribute mean-variance profit differences to differences in managers' risk attitudes, when there is actually unaccounted for inter-firm variation stemming from, say, differences in managerial ability.

We estimate models for two types of profit measures: the ratio of profit to output, and of profit to capital. The latter formulation follows from theory and empirical restricted profit function specifications, while the former is also useful given the skewness in the distributions of profit rates (profit to capital), and possible measurement problems for the capital stock. For both types of models we find that firms with more risk averse managers who face high uncertainty have lower profit variability and lower mean profits. Theory predicts that the higher the risk aversion indicator, the greater should be the attempt at profit smoothing (lower variance) with attendant lower expected profits. While the magnitudes of our estimated coefficients were not strictly consistent with this pattern, there was a marked tendency for mangers choosing more risk averse lotteries to be associated with larger negative effects on firm profit means and variances. The risk aversion coefficients were always jointly significantly different from zero, as was the managerial uncertainty measure (except for one case).

The results indicate that variation in managerial risk attitudes and uncertainty will have economically important effects on the level and variance of profits. The implied mean-variance differences for the most risk averse manager relative to the least risk averse are actually surprisingly large. We have not rejected these quantitative effects as unreasonable, however, as we know from other studies that there is significant inter-firm variation in profit to capital ratios in African manufacturing.

Although the data set contains very limited data on managerial wealth, we attempted to explore wealth effects by including dummies for whether the manager owns a house or a motor vehicle. If wealth facilitates ex post consumption smoothing or if relative risk aversion is decreasing in wealth, the theoretical framework implied that higher managerial wealth will be associated with a portfolio shift into high-risk, high return activities. We found that owning a motor vehicle was associated with higher profits and profit variance in six of the eight cases, while house ownership was generally insignificant.[28] One possible reason why the house ownership dummy did not work very well in the regressions could be that houses differ widely in values, reflecting widely differing wealth levels. Motor vehicles probably differ less widely in values, implying that the dummy for ownership of a motor vehicle would be a better wealth proxy than the dummy for house ownership.

If we accept these findings on the role of risk aversion in Ghanaian firms' strategies for managing risks, there may be a number of important implications for other aspects of firm performance. First, in addition to irreversibilites, risk aversion may help explain the negative effect of uncertainty on investment; or be associated with low investment rates more generally. Second, it may be that risk aversion and the tendency to choose safe, lower-return, lower variance activities, as demonstrated in this paper, is associated with a reluctance to adopt newer, riskier technologies that may have contributed to the record of little or no productivity gains. Clearly, these are areas that remain to be explored.

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APPENDIX

The Data

The data used in the empirical analysis is a sub-sample of the 1991-1995 Ghanaian RPED/GMES panel data set, collected by a team from the Centre for the Study of African Economies (CSAE), University of Oxford, the University of Ghana, Legon, and the Ghana Statistical Office. With two exceptions, all empirical results in the paper are based on data from the two-year period 1994-1995. The first exception refers to the calculations of the correlations between profit means and standard deviations discussed in Section 3, which are based on the five years of data available; the second exception refers to the ordered probit results in Table 4, which are based on one year only (see notes below the tables for more details).

The experimental gambling data were collected in the 1994-95 survey for 91 small and medium-sized firms. We delete 13 of these due to missing data in key variables or substantial measurement errors (see below for sample selection criteria), leaving a sample of 78 firms and a total of 152 observations. We refer to this as the "Full Sample". Whenever we report results based on fewer observations, this is indicated in the table notes.

The variables used in the empirical analysis are defined as follows.

i) *Profit*. Calculated as output value minus the sum of costs for raw materials, indirect costs and wages.

ii) *Capital*. Replacement value of equipment and machinery.

iii) *Wage*. The total annual wage bill divided by the number of employees.

iv) *Employment*. Total number of workers.

v) *Managerial uncertainty*. Subjective variance of expected demand growth one year ahead, calculated from firms' assigned probabilities to each of the following percentage changes in demand: decrease by more than 30%; decrease by 20 to 30%; decrease by 10 to 20%; decrease by 0 to 10%; no change; increase by 0 to 10%; increase by 10 to 20%; increase by 20 to 30%; increase by more than 30%. To calculate the variance, we then use the formula $V_i^E = \sum_j p_{ij} v_j^2 - (\sum_j p_{ij} \mu_j^E)^2$, where p_{ij} is the probability assigned by firm *i* to interval *j*, and v_j^2 and μ_j^E are the second moment (around the origin) and the mean, respectively, of the percentage change within interval *j*. Since we do not have within interval data, we assume a uniform distribution on [l_j, u_j], where l_j and u_j indicate the lower and upper bounds, respectively, of interval *j*. It follows that $\mu_j^E = 0.5(l_j + h_j)$ and $v_j^2 = (h_j^3 - l_j^3) \big/ (3h_j - 3l_j)$. For the open intervals "decrease by more than 30%" and "increase by more than 30%", we set the missing boundaries to 50%.

vi) *Lottery data*. See Section 3. In Tables 5 and 6, "High risk aversion" is a dummy variable equal to 1 if the respondent chose Lottery 1 or Lottery 2, as described in Table 2, and "Intermediate risk aversion" is a dummy variable equal to 1 if Lottery 3 or 4 was chosen.

vii) *Firm age*. Number of years the firm has been in operation.

viii) *Managerial background variables*. a) Industry experience: Calculated as firm age plus manager's years of experience in the industry prior to founding or acquiring the firm. b) Education: Measured in years and derived from responses regarding the highest level of education completed by the entrepreneur, where primary = 6 years; middle school=10 years; secondary = 14 years; university=19 years; secondary plus vocational = 15 years; and secondary plus polytechnic = 16 years. These definitions follow Teal (1998). c) Father had business: Dummy variable equal to one if the respondent's father has owned a business in manufacturing, trading, or farming, and zero otherwise.

ix) *Control Variables*. Industry sector dummies are equal to 1 if the firm belongs to the indicated sector, and zero otherwise. Solo or partnership and Location in Accra are dummy variables equal to one if the dummy category applies for the firm or observation, zero otherwise.

All nominal values have been converted into real USD using PPP adjusted real exchange rates as reported by Bigsten et al. (2000). These numbers are shown in Table A.1.

Table A.1 Exchange Rates and PPP:s, Ghana 1991-1995

	1991	1992	1993	1994	1995
PPP Consumption (%)	40.1	37.0	31.1	25.8	34.1
PPP Investment (%)	101.0	90.3	75.8	62.9	83.1
Exchange Rate (Cedis/US$)	367.8	437.1	649.1	956.7	1200.4

Source: Bigsten et al. (2000).

Sample Selection

The lottery data were only collected for small and medium-sized firms, which involved 91 firms. For some of these there are missing data on one or several relevant variables used in the analysis, and in a few cases there are apparent and sizeable measurement errors in key variables. Such observations were deleted from the two-year panel of 91 firms and 182 observations, according to the following principles: missing data on any of the control variables in (ix) above (2 observations); missing data on the capital stock, profit, wages, or firm age (15 observations); more than 200 employees (2 observations); the capital to value-added ratio smaller than 0.02 (7 observations); and missing data on subjective variance (4 observations). The elimination of these 30 observations leaves a sample of 152 observations associated with 78 firms.

The Likelihood Function

The likelihood function of the model described in 4.2 is formed as follows. Conditional on the random effect, the likelihood contribution of firm *j* over the span of the panel *t*=1,2, is given by

(10) $$f_j^c = \prod_{t=1}^{2} \left(2\pi\sigma_{jt}^2\right)^{-1/2} \exp\left\{-\frac{\left(y_{jt} - h\left(x'_{jt}\beta, \gamma_1\mu_j\right)\right)^2}{2\sigma_{jt}^2}\right\},$$

where $\sigma_{jt}^2 = \sigma^2 \exp\left(z'_{jt}\alpha + \gamma_2\mu_j\right)$ from (9). Integrating this expression over the discrete distribution of the random effect yields the unconditional likelihood contribution

(11) $$f_j = \sum_{m=1}^{M} PI_m \cdot f_j^c\left(\mu_m\right),$$

and maximum likelihood estimates are then obtained by maximising the sample likelihood, given by $f = \prod_i f_i$. Hence the support points, the factor loadings, and their probabilities are estimated along with the other parameters of the model. To estimate the model it is necessary to impose some identifying restrictions. To this end we follow Blau (1994). First, due to the inclusion of an intercept in the model, only M-1 points of support for μ are identified. These support points are parameterised as $\mu_m = \theta W_m$, where θ is a scale factor, W_1 = -0.5, W_M = 0.5, and $W_m = 1/\left(1+\exp\left(a_m\right)\right) - 0.5$, m = 2,…,M-1. Second, we set one of the factor loadings, γ_1, to unity. Third, to constrain the probability terms to be non-negative and sum to unity, we specify appropriate boundary and linear equality constraints in the computer code.[29]

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Table 1. Sample Characteristics

	Mean, pooled observations	Median, pooled observations	1st quartile, pooled observations	3rd quartile, pooled observations	Mean of firm means
Profit / Output	0.17	0.15	0.07	0.23	0.17
Profit / Capital stock	5.50	1.88	0.68	6.08	5.65
Employment	20.2	10	5	22.5	19.9
Capital stock	164,006	4,179	1,360	29,993	160,784
Wages	983	712	352	1,340	997
Firm age	14.7	13.5	6	20	14.7
Foods¤	0.20				0.21
Textile¤	0.29				0.30
Metal¤	0.28				0.27
Wood¤	0.24				0.23
Accra¤	0.43				0.42
Solo or partnership¤	0.80				0.81
Year 1995¤	0.51				
Observations	152	152	152	152	78

Notes:
Nominal values have been PPP converted to USD, see Table A.1 in Appendix.
¤ Dummy variable.

Table 2. Lottery Payoffs and Risk Classification

Lottery	Outcome: Heads	Outcome: Tails	E (x)	$\sigma(x)$	Risk Aversion Class*	S Risk Aversion Coefficient	Trade-off: $Z=\Delta E(x)/\Delta\sigma$
1	1000	1000	1000	0	Extreme	∞ to 7.51	1 to 0.80
2	900	1900	1400	500	Severe	7.51 to 1.74	0.80 to 0.67
3	800	2400	1600	800	Intermediate	1.74 to 0.812	0.67 to 0.50
4	600	3000	1800	1200	Moderate	0.812 to 0.316	0.50 to 0.33
5	400	3200	1800	1400	Inefficient		
6	200	3800	2000	1800	Slight-to-neutral	0.316 to 0	0.33 to 0.00
7	0	4000	2000	2000	Neutral-to-negative	0 to -∞	0 to -∞

Notes:
In 1995, 1000 Ghanaian Cedis was equivalent to USD 2.44 (PPP adjusted). According to Bigsten et al. (1999), the average monthly earnings in Ghanaian manufacturing was equal to PPP USD 160 in 1994. Hence, a favourable outcome in Lottery 7 would correspond to a little more than one day's average earnings.
* As defined by Binswanger (1980).

Table 3. Managerial Uncertainty of One Year Ahead Expected Output

Subjective Variance (%)	Proportion of Firms
0< ≤10	0.55
10< ≤20	0.23
20< ≤30	0.08
30< ≤40	0.03
40< ≤50	0.04
>50	0.08
Number of firms (N)	78

Notes:
See appendix for details on how subjective variance has been calculated.

Table 4. Ordered Probit Results for Lottery Selection

	Coefficients	Effects on Predicted Probabilities [#]		
		$\Delta P(RA=1) / \Delta X$	$\Delta P(RA=2) / \Delta X$	$\Delta P(RA=3) / \Delta X$
Log capital	0.036	-0.014	0.002	0.012
	(0.099)	(0.037)	(0.007)	(0.032)
Manager's industry experience	0.044***	-0.016***	0.002	0.014***
	(0.015)	(0.006)	(0.002)	(0.005)
Manager's education	0.087*	-0.033*	0.005	0.028*
	(0.051)	(0.019)	(0.006)	(0.016)
Manager's age	-0.034*	0.013*	-0.002	-0.011*
	(0.020)	(0.007)	(0.002)	(0.007)
Father had business[¤]	0.595*	-0.230*	0.056	0.174*
	(0.347)	(0.125)	(0.049)	(0.09)
Owns house	-0.418	0.159	-0.027	-0.132
	(0.387)	(0.142)	(0.038)	(0.114)
Owns motor vehicle	-0.390	0.149	-0.027	-0.121
	(0.435)	(0.158)	(0.037)	(0.131)
Sole proprietorship or partnership[¤]	0.429			
	(0.492)			
Location in Accra[¤]	-0.013			
	(0.356)			
Food[¤]	-1.006**			
	(0.509)			
Textile[¤]	-0.949*			
	(0.502)			
Metal[¤]	-0.756*			
	(0.443)			
Constant	0.074			
	(1.364)			
Threshold 1	0.969***			
	(0.181)			
Log likelihood		-64.4		
$\chi^2(10)$		23.9**		
Number of observations (firms)		67 (67)		

Notes:

Eleven firms were dropped from the sample due to missing values in at least one of the explanatory variables used in the regression.

The numbers in ( ) are standard errors. The standard errors of the model coefficients are robust, calculated using the standard sandwich formula (White, 1982), whereas the standard errors of the marginal effects were generated by a simulation (see below). Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

[#] Evaluated at sample means. For continuous variables the point estimates are marginal effects, and for dummy variables the numbers are the estimated probability changes associated with a discrete change from zero to one. To generate standard errors we drew a vector of random normal variates with mean equal to the coefficient point estimates, and covariance matrix given by the (robust) covariance matrix of the coefficient estimates. We repeated this process 1,000 times to generate distributions of the effects on probabilities. The reported standard errors are the standard deviations of the simulated marginal effects over the 1,000 replications.

[¤] Dummy variable.

Mean values (standard deviations) of variables used in regression: Lottery group 1=0.39; Lottery group 2=0.31; Lottery group 3=0.30; Log capital=8.7 (2.3); Experience=21.1 (13.7); Education=9.8 (4.3); Age=44.7 (11.3); Father had business=0.73; Owns house=0.40; Owns motor vehicle=0.36; Solo or partnership=0.82; Accra=0.43; Food=0.18; Textile=0.27; Metal=0.30. (Standard deviations omitted for dummy variables.)

Table 5. Random Effects Estimates: Profit to Output Ratio and Variance

	(a) Risk aversion excluded		(b) Risk aversion included	
	Coefficient	Std. Error	Coefficient	Std. Error
A. Profit Equation				
Constant	0.037	0.029	0.078***	0.020
Food	-0.027*	0.015	0.006	0.014
Textile	-0.045**	0.018	-0.035***	0.013
Metal	-0.063***	0.019	-0.036**	0.014
Log capital stock	0.015***	0.002	0.014***	0.001
Solo or partnership	0.085***	0.018	0.088***	0.005
Firm age / 10	0.004	0.010	0.014***	0.005
Located in Accra	-0.061***	0.020	-0.033***	0.011
Year 1995	0.001	0.009	0.000	0.008
Owns house	0.021	0.015	-0.006	0.013
Owns motor vehicle	0.041**	0.017	0.038***	0.008
Subjective variance	-0.016***	0.004	-0.012***	0.003
High risk aversion			-0.064***	0.016
Intermediate risk aversion			-0.102***	0.009
B. Variance Function				
σ	0.078*	0.043	0.309	0.232
Food	1.003**	0.417	1.607***	0.582
Textile	-0.266	0.638	-0.299	0.564
Metal	0.513	0.519	1.095**	0.528
Log capital stock	0.088	0.142	-0.083	0.149
Year 1995	-0.582	0.397	-1.796**	0.734
Owns house	-0.968	0.755	-0.967	0.612
Owns motor vehicle	1.567**	0.628	2.278***	0.521
Subjective variance	-0.803***	0.130	-1.024***	0.162
High risk aversion			-1.731***	0.522
Intermediate risk aversion			-1.443***	0.443
C. Auxiliary Parameters				
θ	0.210***	0.025	0.187***	0.013
γ_1	1.000	---	1.000	---
γ_2	10.527***	3.424	1.920	3.405
a_1	-0.458*	0.276	0.009	0.167
PI_1	0.273***	0.075	0.556***	0.107
PI_2	0.563***	0.110	0.306***	0.088
PI_3	0.164**	0.065	0.138**	0.058
Log Likelihood	161.2		171.0	
NT (N)	148 (77)		148 (77)	

Notes:

Standard errors are robust, computed using the standard sandwich formula (White, 1982). Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Four observations with extremely high profit rates (between 0.68 and 0.93) have been eliminated from the sample. In the estimation sample, the highest recorded profit rate is 0.48. Results including the four outliers are available on request.

Table 6. Random Effects Estimates: Short-Run Profit Function and Variance

	(a) Risk aversion excluded		(b) Risk aversion included	
	Coefficient	Std. Error	Coefficient	Std. Error
A. Profit Function				
Constant	-0.115	0.624	-1.071*	0.558
Foods	-0.132	0.231	0.954***	0.095
Textile	-1.095***	0.164	-0.146	0.127
Metal	-0.290**	0.117	0.482**	0.204
Log average wage	-0.052	0.057	0.052	0.069
Solo or partnership	0.411**	0.181	0.549***	0.167
Firm age	-0.003	0.003	0.020***	0.002
Located in Accra	-0.214	0.177	-0.588***	0.134
Year 1995	0.009	0.170	-0.285**	0.139
Owns house	-0.003	0.175	-0.179**	0.081
Owns motor vehicle	-0.122	0.155	0.145	0.089
Subjective variance	-0.101	0.062	-0.324***	0.039
High risk aversion			-0.591***	0.144
Intermediate risk aversion			-1.392***	0.124
B. Variance Equation				
σ	0.993***	0.321	0.229**	0.115
Foods	1.261*	0.654	2.738***	0.693
Textile	-1.296**	0.592	1.517*	0.840
Metal	-0.333	0.577	3.477***	0.694
Log employment	-0.433	0.296	-0.297*	0.180
Year 1995	-1.110*	0.617	1.248*	0.665
Owns house	-1.412***	0.482	-0.346	0.605
Owns motor vehicle	1.254*	0.724	1.365***	0.405
Subjective variance	-0.310*	0.188	-0.841***	0.221
High risk aversion			-2.118***	0.454
Intermediate risk aversion			-3.426***	0.533
C. Auxiliary Parameters				
θ	7.181***	0.556	7.072***	0.275
γ_1	1.000	---	1.000	---
γ_2	1.615***	0.142	2.014***	0.148
a_1	1.469***	0.143	1.778***	0.258
a_2	0.617***	0.198	0.803***	0.093
a_3	0.013	0.151	-0.379***	0.108
PI_1	0.058**	0.028	0.038*	0.022
PI_2	0.349***	0.078	0.344***	0.065
PI_3	0.191***	0.065	0.325***	0.063
PI_4	0.253***	0.059	0.217***	0.054
PI_5	0.150***	0.047	0.077**	0.035
Omitted variables[(a)]: $\chi^2(8)$	22.14***		7.94	
Endogeneity[(b)]: z			0.08	
Log Likelihood	-333.0		-319.5	
NT (N)	152 (78)		152 (78)	

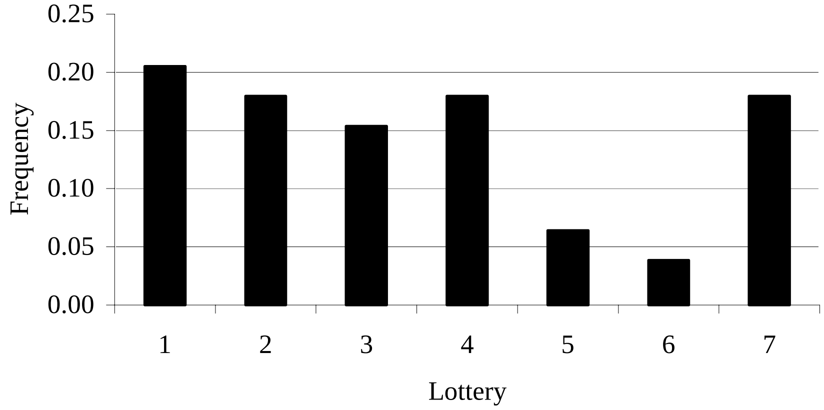
Notes:

Standard errors are robust, computed using the standard sandwich formula (White, 1982). Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

[(a)] Wald test of the hypothesis that manager's age, education, industry experience, and the dummy for whether the father had a business can be excluded from the profit and variance specifications. To carry out the test without discarding observations, missing values in these variables were replaced by sample means.

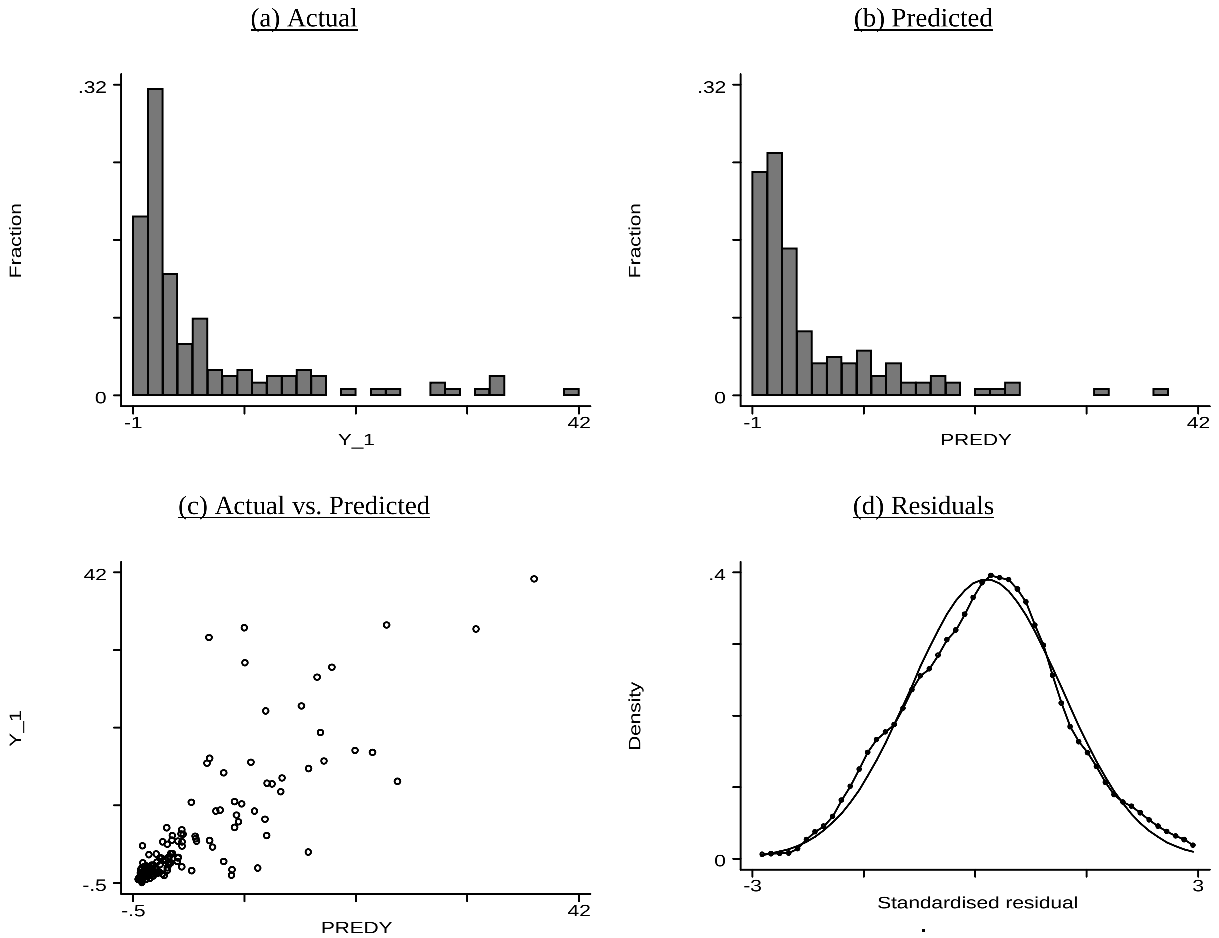
[(b)] Tests whether risk aversion dummies are endogenous, as described in the main text.

Figure 1. Sample Distribution of Lottery Selections



Notes:
Lottery 1 has the lowest expected return and variance, and Lottery 7 has the highest (see Table 2).

Figure 2. Diagnostic Plots for Model (b) in Table 6



Notes:

To calculate the predictions we follow the approach outlined in Deb and Trivedi (1997), which is as follows. Conditioned on the estimated probability coefficients $PI_1,\ldots, PI_5$ we calculate the posterior probability that observation y_i belongs to class m=1,…,5 using the formula $PI_m f_{im}^c(\mu_m) \big/ \sum_j PI_j \; f_{ij}^c(\mu_j)$. The highest probability for each firm indicates the heterogeneity class to which the firm belongs, and predicted values are then computed conditional on the appropriate class for each firm

[1] That is, a mean-variance trade-off. If this is not the case, there will be corner solutions where the manager allocates zero-shares to some activities (alternatively, possibly a unity-share to one single activity).

[2] RB use data on Indian farms to test their theory. It should also be noted that this is one of the few studies that provides information on the costs of risk reduction, in terms of foregone average profits.

[3] However, there certainly may be cases where diversification leads to higher profits, depending on other factors such as the firm size, age, and type of industry.

[4] The third of these implications has also been highlighted in the agricultural household literature. In particular, it has been shown that households' differing abilities to smooth consumption ex post will affect the attractiveness of using portfolio diversification, with its attendant costs, to reduce income variability. Households more likely to be credit constrained in the future, or without large stocks of liquid assets, will be more inclined to trade income variability for stability (Dercon, 1996, Morduch, 1990).

[5] See Teal (1998) for details on the survey. At the time of writing, the first three waves of the data can be downloaded from the web at http://www.csae.ox.ac.uk/.

[6] For this computation we used data spanning the period 1991-95, in order to compute the standard deviation as accurately as possible.

[7] Fifty-seven individuals chose the same lottery when the game was played for real money as they had chosen in the hypothetical game. Twelve individuals switched to a less risky lottery, and nine switched to a more risky lottery, when the game was for real money. In the remainder of this analysis we will use the data from the actual gamble.

[8] Of course, this objection ignores the fact that in low-income countries, it would be infeasible and undesirable to implement surveys where participants lose their own money.

[9] We also tried with additional explanatory variables, such as a dummy for borrowing in informal credit markets, gender, and number of years of residence in the current town. However, none of these had significant coefficients. Because of the small sample size it is desirable to keep the model relatively small and simple, and therefore we have excluded these additional variables in the regression reported in Table 4. The results of the more general model are available on request.

[10] Industry experience is defined as firm age plus experience prior to founding or acquiring the business (see Appendix). When these two variables are entered separately, the null hypothesis that they have equal coefficients cannot be rejected at the 10% level of significance (p-value = 0.93).

[11] A more restrictive version of this heteroskedasticity model, not allowing for unobserved heterogeneity, is discussed by Greene (1993), pp. 401-402. For applied work using the latter model, see e.g. Fafchamps and Pender (1997).

[12] The factor loading technique means that we effectively allow for correlation between the unobserved mechanisms affecting the variance of the residual and those affecting profits (positive correlation is indicated by γ_1 and γ_2 having equal signs, and vice versa). This is attractive for many reasons; for instance, if our data on risk aversion only partially measure true risk aversion (so that a portion of risk aversion remains unobserved), one would expect this correlation to be positive, due to the mean-variance trade-off.

[13] The empirical literature based on discrete factor approximations is growing rapidly. See for instance Moon and Stotsky (1993), Blau (1994), Ham and LaLonde (1996), and Deb and Trivedi (1997).

[14] Clearly, whenever the reported value of the capital stock is substantially lower than the true value, the profit to capital ratio will be heavily inflated.

[15] Note that we take both risk aversion and uncertainty, as measured by the lotteries and the subjective variance, to be time invariant. This is perhaps not strictly correct, but it does not seem too strong to assume these variables to be slow changing, so over such a short period as two years it will probably not lead to too misleading results.

[16] As explained in the appendix, estimation of the model requires some normalisations. One is to set γ_1 = 1, which is reflected in (4).

[17] There are no well-established criteria for determining the number of support points *M* in models like these (see e.g. Heckman and Walker, 1990), so we follow standard practice and increase *M* until there are only marginal improvements in the log likelihood value. For the regressions shown in Table 5, the addition of a fourth point yielded only a minor increase in the log likelihood value, and the estimated probability coefficient associated with the fourth point was very close to zero.

[18] The Wald test statistic that the two risk aversion coefficients are the same is equal to 11.4, hence we reject the hypothesis that they are equal.

[19] To assess the appropriateness of assuming constant returns, we estimated the Cobb-Douglas production function directly. Regressing the log of value-added on employment, capital (in logs), and control variables for industry, location, and firm status, we could not reject constant returns in capital and employment at the 10% level (the p-value was equal to 0.82). Results are available on request.

[20] Indeed, when the model is estimated without unobserved heterogeneity, the coefficient on log employment in the variance equation is equal to –1.2, and significant at the 1% level.

[21] However, it is also clear that the coefficient on intermediate risk aversion is substantially lower than that on high risk aversion, which runs counter to the monotonic pattern predicted by theory. It is difficult to say whether this is due to imperfect mapping of risk attitudes into lottery choices, or because of some other data anomaly. Perhaps strict monotonicity is simply too much to expect from the data. Nevertheless, based on our results we can firmly reject the hypothesis that risk aversion is an irrelevant variable for the level and variance of profits.

[22] According to theory, the wage coefficient should be negative (see eq. 7), yet it is not unusual to see positive wage coefficients in the empirical literature (e.g. Westley and Shaffer, 1999). One reason advanced is that there are efficiency wages.

[23] As indicated in the table notes, missing values in the background variables have been replaced by sample means here in order not to lose observations.

[24] Regressing actual profit rates on predicted profits and a constant, we cannot reject the hypothesis that the coefficient on predicted profits is unity at the 10% level of significance.

[25] The Shapiro-Wilk (1965) test statistic for normality, as reported by the STATA package, is equal to -0.578, and the associated p-value is equal to 0.72.

[26] To check functional form sensitivity, we assumed the error term to be multiplicative and log-normally distributed (instead of additive, as in eq. 8). We then estimated a log-linear version of the profit function by OLS (in this case we had to add a fixed constant to all profit rates so that there is no negative dependent variable). The estimated coefficient on intermediate risk aversion was –0.93, which is slightly less substantial than in Table 6 but still of considerable size, implying that the expected profit rate will be 39% of that of the least risk averse category.

[27] Calculated as $[\exp(-2.118)]^{0.5}$.

[28] An important finding of Rosenzweig and Binswanger (1993) was that the tendency to shift to a less risky, less profitable portfolio was greater for households with less wealth, and not as important for the wealthy, who have greater access to credit markets and buying and selling personal assets to smooth consumption ex-post. Over time, these patterns contribute to further widening of income and wealth differences.

[29] These models are coded in SAS/IML. We use the built-in Newton-Raphson Ridge Optimization Method (NLPNRR) to maximise the likelihood function. We guard against convergence at a local maximum by using several different start values for each model.