Risk Preferences and Job Mobility in Zimbabwe

Leon Matsuro¹, Neil A. Rankin² Working Paper July 2019

Abstract

Job mobility is a fundamental characteristic of labour markets. The decision to quit and move to another job is inherently risky, as workers have limited ex ante information of the quality of outside jobs. Canonical models on job mobility assume risk neutrality, however, risk aversion potentially affects workers' mobility decisions thorough influencing job acceptance (reservation match quality) and job search (search effort). This paper integrates concepts from the risk and job mobility literatures to investigate the empirical relationship between risk aversion and job mobility in an economic environment characterised by uncertainty. To answer this important question, we use Zimbabwean matched employer-employee panel data set (2015-2016), which includes experimentally elicited risk preferences measures. Our empirical approach involves estimating the basic mobility model using the traditional economic variables and controlling for individual heterogeneity in risk preferences. Our results show that risk averse workers are less likely to experience job mobility compared to their risk tolerant peers. This relationship is robust to the inclusion of human and job characteristics known to explain job mobility. The study broadens our understanding of employment dynamics in developing countries' characterised by economic uncertainty. Furthermore, it contributes to the recent debate on how heterogeneity in risk preferences explain variations in economic outcomes in particular those related to labour markets.

Keywords: Risk aversion, job mobility, uncertainty

JEL Classification: D81, J63

¹ PhD Candidate, Graduate School of Economic and Management Sciences, Economics Department, Stellenbosch University

² Professor Economics Department, Stellenbosch University

1.0. Introduction

Risk and uncertainty are central in almost every important aspect of economic decision-making. This is particularly true in labour markets where workers decide between staying and moving to another job. Job mobility plays an important role in the efficient functioning of labour markets (Mortensen, 2011); as such, knowledge of how workers make decisions related to moving between jobs is important. The drivers, and subsequent positive effects of job mobility on wages has been explored by theoretical models (e.g. Burdett, 1978; Johnson, 1978; Jovanovic, 1979) and largely supported by empirical literature (Fuller, 2008; Neumark, 2002; Pavlopoulos, Fouarge, Muffels & Vermunt, 2014; Topel & Ward, 1992). Existing theoretical models on job mobility possibly miss some important information on workers' job changing behaviour as they assume homogenous risk preferences and concentrate on observable individual and job characteristics. Recently interest has grown in identifying additional measures that could explain employee mobility. A major issue addressed in this literature is the role of risk preferences (Argaw, Maier & Skriabikova, 2017; van Huizen & Alessie, 2016; Vardaman, Allen, Renn & Moffitt, 2008).

Following a study in Netherlands by van Huizen and Alessie (2016; VH&A hereafter), this study examines the empirical relationship between risk preferences and job mobility under conditions of economic uncertainty. Job changes are risky and involve uncertainty. VH&A derive predictions on the relationship between risk aversion and job mobility through two main channels mainly; job search and job acceptance. Even after accounting for anticipated costs and benefits of job mobility, a worker's benefits from a job change are not fully determined ex-ante. We argue that individuals' willingness to take risk is key in explaining job mobility behaviour in the labour market. In order to throw light on these matters, the study presents new data on risk preferences from a developing country characterised by economic uncertainty. The novel matched employer-employee panel data set from Zimbabwean manufacturing sector contains information on individuals' labour markets experiences and a range of background characteristics. In addition, it contains information on individuals' risk preferences elicited through incentivised lab-in-the-field experiments.

Empirical evidence on the role of risk preferences in explaining mobility decisions under conditions of economic uncertainty within a developing country context is virtually non-existent. To our knowledge, a few studies empirically examine the effects of risk aversion on job mobility (Argaw *et al.*, 2017; van Huizen & Alessie, 2016; Vardaman *et al.*, 2008). However, except for Falco (2014) who investigates occupational sorting, existing literature is biased towards developed countries whose labour markets differ remarkably from developing countries. Some of the studies rely on survey type of measures (Argaw *et al.*, 2017) as well as hypothetical lotteries to capture individuals risk attitudes. While convenient, hypothetical gambles hinge on the assumption that subjects have knowledge of how they would behave in real world situations where they have to make choices, and that they have no motive to hide their true preferences (Kahneman & Tversky, 1979). This may not always be the case. We address these issues by presenting subjects with incentivised simple choice tasks designed to capture risk attitudes.

A critical step in investigating the role of risk preferences in workers' mobility decisions involves developing empirically valid measures of risk preferences. In this study, we follow previous literature (Cramer *et al.*, 2002) and adopt the Arrow-Pratt (Pratt, 1979) measure of absolute risk aversion to estimate individuals risk aversion. As an initial step, we check for sources of heterogeneity in risk preferences by a set of standard demographic characteristics.

We establish that risk preferences vary by one's sector of employment, their ethnicity and geographical location. The study turns to a more systematic regression based type analysis of the relationship between risk preferences and job mobility. We estimate the standard mobility model and control for risk preferences. In line with our hypothesis, we find that risk averse workers are less likely to experience job mobility. Previous studies also confirm this relationship (Argaw *et al.*, 2017; van Huizen & Alessie, 2016). The results suggest that models that seek to describe observed labour market flows should allow for individual heterogeneity in risk attitudes.

The study contributes to the recent debate on how heterogeneity in risk preferences explain variations in individuals' economic outcomes in particular those related to labour markets. Employee mobility is an important variable in labour economics as it relates to wages and careers (Pavlopoulos *et al.*, 2014; Pfeifer, 2010; Topel & Ward, 1992); the results thus have important implications on individuals' labour market success. Given the recent interest in exploring the risk aversion – job mobility nexus and subsequent wage growth (Argaw *et al.*, 2017), the study offers new insights on the possible mechanisms constraining or aiding income growth in developing countries.

In addition, it broadens our understanding of the literature on labour market dynamics in countries characterised by economic uncertainty. Focusing on Zimbabwe makes it a particularly interesting case. Zimbabwe is currently going through one of its worst and prolonged episodes of economic challenges. Amongst the most adverse and enduring effects of decades of Zimbabwe's economic malaise is the increase in long-term unemployment and the simultaneous contraction of formal sector and expansion of the informal sector (ZIMSTAT, 2015). Unlike developed countries that typically have tight labour markets, alternative job offers are difficult to find in an economically struggling country like Zimbabwe. Given these economic conditions, quitting a job may be significantly risky as the likelihood of becoming unemployed while queuing for job offers is high. On the other hand, the relatively free entry informal sector is equally associated with income uncertainty (Bennett, Gould & Rablen, 2012; Falco, 2014). Unsurprisingly, a significant portion of the worker sample (40%) report being owed (outstanding salaries) by their firms but continue to report for work. This may imply that to these individuals quitting a job (even a bad one) is more risky than staying. Empirical evidence shows that being unemployed for a long time comes with an emotional toll, especially for married man (Basbug & Sharone, 2017). For these reasons, risk aversion may be a critical factor in explaining labour dynamics in developing countries.

We structure the remainder of the study as follows. Section 2 discusses job mobility theories, findings from previous literature, and spells out the conceptual framework. We discuss the data and methodological framework adopted in this study in section 3. Section 4 reports the results from the probit model estimation of the effects of risk aversion on job mobility and discuss the findings. Section 5 concludes.

2.0. Theoretical models on employee mobility

In labour economics, on-the-job-search and job matching models form the theoretical basis of studying job mobility. Individuals search for jobs and accept offers when the value (wage) of the new job is higher than the present job (Burdett, 1978; Jovanovic, 1979). In essence, workers transition between jobs to improve their current situation. The predictions of search models imply lower job transitions with increasing age as workers are more likely to have searched and found better jobs. Hwang, Mortensen and Reed (1998) introduce nonwage components in

the on-the-job search framework signifying the importance of job characteristics. These characteristics include hours worked, working time, work environment and employment conditions. Subsequent empirical analyses confirm the importance of nonwage job characteristics on individuals' decision to change jobs (e.g. Baird, 2017; Bonhomme, Jolivet & Leuven, 2016; Sullivan & To, 2014).

The principal concern of this literature was to account for the role of observable human and job characteristics in explaining individuals' job changing behaviour. The models have undoubtedly increased our understanding of job mobility; however, they may not adequately explain observed differences in mobility patterns amongst workers especially in developing economies. Central to these models is the premise of imperfect information; in most instances, the quality of job match only reveals itself sometime after employee has accepted a job offer. Topel and Ward (1992) show that most job transitions in the early career (often job-to-job) reflect voluntary job changes rather than layoffs. There are "search or information frictions" in the labour market that prevent workers from immediately matching with their optimal job. Even after accounting for foreseen costs and benefits of job mobility, a worker's benefits from a job change are not fully determined ex-ante. Changing one's job especially outside of the present firm is inherently risky. Workers' risk aversion is thus an important factor when evaluating the expected utility from a job switch. Hence, ceteris paribus, risk tolerant individuals are more likely to experience job mobility, because these individuals are more willing to take risk associated with a job change.

2.1. Previous literature

A significant amount of literature focuses on developing empirically validated measures of individuals risk attitudes (Holt & Laury, 2002, 2014; Lönnqvist, Verkasalo, Walkowitz & Wichardt, 2015; Thomas, 2016). This has broadened our appreciation of dimensions of individuals' unobservable heterogeneity³. However, questions remain. One important question relates to the determination of individuals risk attitudes using experimentally elicited measures involving real monetary payoffs in the context of developing countries. Some studies rely on survey type of questions, typically self-ratings on a Likert scale (Dohmen, Falk, Huffman & Sunde, 2010), while others rely on hypothetical gambles. Because these methods are not incentive compatible, there is scepticism on whether they capture individuals' truer attitudes to risk. A number of factors could possibly distort individuals' reported risk attitudes, including self-serving biases and inattention (Camerer & Hogarth, 1999). To address these concerns, incentive compatible experimental measures have been developed (Holt & Laury, 2002, 2014).

Theoretical models on labour markets are silent on individuals' attitudes to risk or assume that workers are risk neutral. However, emerging literature documents the significance of risk preferences in explaining a variety of life outcomes including health, migration, education and labour market outcomes. Labour markets studies have focused on selection into self-employment (Ahn, 2010; Caliendo, Fossen, Kritikos, M & Á, 2009; Ekelund, Johansson, Järvelin & Lichtermann, 2005; Skriabikova, Dohmen & Kriechel, 2014), sectorial choice (Falco, 2014) and occupational choice (Fouarge, Kriechel & Dohmen, 2014). Others on choice of employment contract (Dohmen and Falk, 2011), job mobility (Argaw *et al.*, 2017; van Huizen & Alessie, 2016) and earnings (Bonin, Dohmen, Falk, Huffman & Sunde, 2007; Cho, 2012; Kim & Lee, 2012). Evidence from these studies shows that differences in risk attitudes have considerable effects on labour market outcomes.

-

³ Other measures include non-cognitive skills encompassing personality traits, locus of control and time preferences

Studies on selection into self-employment report that risk tolerant individuals are most likely to be self-employed (Ahn, 2010; Caliendo *et al.*, 2009; Ekelund *et al.*, 2005; Skriabikova *et al.*, 2014). The empirical literature largely reports a wage premium for risk-loving individuals (Ahn, 2010; Bonin *et al.*, 2007). The effect on wages can be explained indirectly through occupational choices. The wage premium has been confirmed to be robust to controls for heritability and family background (Le, Miller, Slutske & Martin, 2014). Risk averse individuals are more likely to work in the formal sector (Bennett *et al.*, 2012; Falco, 2014). Interestingly, studies report that gender differences in risk attitudes indirectly explain gender differences in labour market outcomes. For instance, women are reported to be more risk averse than men (Dohmen et al. 2011; Cardenas & Carpenter 2013; van Huizen 2013), are less likely to select into self-employment (Ekelund *et al.*, 2005) and their risk attitudes account for some of the gender wage gap (Le et al. 2010).

Literature on the effects of risk aversion on job changes is scarce. We only know of few studies that model the relationship between risk attitudes and job mobility (Argaw et al., 2017; van Huizen & Alessie, 2016; Vardaman et al., 2008). Using German data Skriabikova, Argaw and Maier (2017) develop risk preference measures based on survey questions and find that risk seeking individuals are more likely to experience job mobility. The study further reports that subsequent wage growth arising from job switches is lower for risk tolerant individuals compared to those that are risk averse. In a related study, van Huizen and Alessie (2016), using a Dutch panel find similar results. Risk aversion inversely relates to job mobility. The study however reports stronger effects for the sample treated to an incentivised experiment compared to those who participated in an experiment with hypothetical payoffs. The finding suggests that incentives helps eliminates some of the noise in the risk measure, which has important implications in empirical analysis. In addition, they report that risk aversion particularly has stronger effect on job mobility for workers on permanent contracts and under tougher economic conditions. Despite using different risk measures, both studies report similar results and offer insights on the importance of accounting for risk attitudes in mobility models.

What is clear from the literature is that work on the effects of risk aversion on job mobility is still developing; more so, it is particularly non-existent for developing countries especially in Sub-Saharan Africa. It is surprising that this literature is scarce in respect of developing countries yet risk preferences may be crucial in explaining the remarkable differences in labour market success in these countries. For instance, empirical evidence shows that risk aversion may result in economic agents foregoing better economic opportunities (Van den Berg et al. 2009) and may slow down the process of economic recovery after a negative economic shock (Dohmen et al. 2016). Given the importance of risk attitudes in explaining life outcomes, the study aims to addresses the empirical vacuum first by determining workers risk attitudes. We then extend the analysis to Zimbabwean labour markets, focusing on observed workers' job changing behaviour.

2.2. Conceptual Framework

In this study, we adopt van Huizen and Alessie (2016) theoretical model that formalises the relationship between risk aversion and job mobility. The model explains two potential channels through which risk aversion influences job mobility mainly: job acceptance (Jovanovic, 1979) and job search (Burdett, 1978).

2.2.1. Risk aversion and job acceptance

Van Huizen and Alessie (2016) model builds on Jovanovic (1979), and argues that individuals possess more information about their current job compared to outside opportunities. To capture the notion of *ex ante* uncertainty of the quality of job match, their model assumes that at any given point in time a job offer y arrives as a random draw from the joint distribution F(y), where $y \sim N(\mu, \delta_{\mu}^2)$. Unlike in the canonical on-the-job-search, the value of the job match is not simplified to the (known) wage, but contains nonwage job characteristics (Sullivan & To, 2014) that determine the (dis)utility derived from holding the job. When a job offer arrives, a worker does not observe the true value of the job. He instead, receives a noisy signal $\hat{y} = y + \varepsilon$, where $\varepsilon \sim N(0, \delta_{\varepsilon}^2)$. A worker is assumed to have perfect information about his current job match and that the value of the job is immediately revealed when offer is accepted.

Upon receiving an outside offer, a worker takes up the job only if the observed signal of the job \hat{y} is higher than the reservation match quality \hat{y}^* . He is indifferent between accepting or rejecting a job offer if:

$$V(y_0) = E[V(y)|\widehat{y} = \widehat{y}^*] \tag{1}$$

where $V(y_0)$ is the utility derived from current job match y_0 and $E[V(y)|\widehat{y}=\widehat{y}^*]$ represents the expected utility value of the reservation match quality \widehat{y}^* . Workers evaluate the expected utility of the new job match differently according to their risk attitudes. Because of the uncertainty of outside jobs, risk averse workers are critical about job offers compared to risk neutral workers as:

$$E[V(y)|\hat{y} = \hat{y}^*] = V[E(y|\hat{y} = \hat{y}^*) - \Pi] < V[E(y|\hat{y} = \hat{y}^*)]$$
(2)

Where Π indicates the risk premium. The link between risk attitudes and reservation match quality can be examined using the following equations:

$$E[V(y)|\hat{y} = \hat{y}^*] = V[E(y|\hat{y} = \hat{y}^*) - \Pi] \cong V[E(y|\hat{y} = \hat{y}^*)] - \Pi V'(E(y|\hat{y} = \hat{y}^*))$$
(3)

$$E[V(y)|\widehat{y} = \widehat{y}^*] \cong V[E(y|\widehat{y} = \widehat{y}^*)] + \frac{1}{2}E(\widetilde{\varepsilon}^2|\widehat{y} = \widehat{y}^*)V''(E(y|\widehat{y} = \widehat{y}^*)) = 0$$

$$V[E(y|\hat{y} = \hat{y}^*)] + \frac{1}{2} \frac{\sigma_{\varepsilon}^2}{\sigma_{\gamma}^2 + \sigma_{\varepsilon}^2} V''(E(y|\hat{y} = \hat{y}^*))$$
(4)

We can derive the function for the risk premium

$$\Pi = \frac{1}{2} \frac{\sigma_{\mathcal{E}}^2}{\sigma_{\mathcal{V}}^2 + \sigma_{\mathcal{E}}^2} A_{\hat{\mathcal{V}}^*} \tag{5}$$

Note that equation (1) and (3) imply that:

$$y_0 = E(y|\hat{y} = \hat{y}^*) - \Pi \tag{6}$$

Using equation 5, equation 6 can be written as⁴:

$$y_0 = E(y|\hat{y} = \hat{y}^*) - \frac{1}{2} \frac{\sigma_{\varepsilon}^2}{\sigma_{v}^2 + \delta_{\varepsilon}^2} A_{\hat{y}^*}$$
 (7)

⁴
$$E(y|\hat{y} = \hat{y}^*) = \frac{\sigma_{\epsilon}^2}{\sigma_y^2 + \sigma_{\epsilon}^2} \mu_y + \frac{\sigma_y^2}{\sigma_y^2 + \sigma_{\epsilon}^2} \hat{y}^*$$

Under the assumption of normality of y and ε , we can express the reservation match quality:

$$\hat{y}^* = y_0 + \frac{\sigma_{\varepsilon}^2}{\sigma_{\nu}^2} \left[y_0 - \mu_{y} + \frac{1}{2} A_{\hat{y}^*} \right]$$
 (8)

Equation 8 shows that individuals' reservation match quality (\hat{y}^*) increases with risk aversion $(A_{\hat{y}^*})$; risk tolerant workers change their jobs more often compared to risk averse workers. The job acceptance decision dictates that a worker accepts a job when the signal from the job offer is greater than the reservation value $(\hat{y} > \hat{y}^*)$. The significance of risk aversion in job acceptance depends on the noise of the signal (δ_{ε}^2) ; if quality of match is perfectly observable $(\delta_{\varepsilon}^2 = 0)$, job mobility will be riskless and involves no uncertainty.

In addition to this, there is a direct relation between the value of the current job match and the reservation match quality. The implication is that individuals in better matches are less likely to move than those in bad matches. The uncertainty in the value of alternative matches (captured by σ_y^2) reduces the reservation match value if the current job match is low (when $y_0 - \mu_y$ is sufficiently negative), but increases the reservation value if the current job match is sufficient high. Uncertainty may thus have two effects depending on current match: encourage workers in bad jobs to quit, and discourage those in good jobs from leaving.

2.2.2. Risk aversion and job search

The model focused on so far assumed job offers are exogenous; however, search intensity determines job arrival rates. Search activities require one's commitment in terms of time and effort, and may be stressful. Theoretically, on-the-job search s involves costs s, defined by an increasing convex function of s, and determines job arrival rates s, where s captures efficiency of search. A worker sets optimal job search effort by equalising marginal costs of search s with marginal benefits of search:

$$c'(s) = \lambda E \int_{\hat{y}^*}^{\bar{y}} [V(y) - V(y_0)] dF(y) = \lambda \left[1 - F(\hat{y}^*) \right] [E(V(y | \hat{y}^*)) - V(y_0)]$$
(9)

If we assume risk aversion does not affect reservation match quality (\hat{y}^*) , search intensity is less for risk averse workers than for risk neutral workers such that;

$$[1 - F(\hat{y}^*)] \big[E(V(y|\hat{y} > \hat{y}^*) \big) - V(y_0) \big] < \big[1 - F(\hat{y}^*) \big] \big[V(E(y|\hat{y} > \hat{y}^*)) - V(y_0) \big] \ (10)$$

The intuition behind this is that risk averse individuals are reluctant to invest in job search since it comes with uncertain rewards. As shown in Subsection 2.2.1, upon receiving an offer, the reservation match quality increases with risk aversion. In equation (10), we also discovered that risk aversion decreases search intensity and thus probability of successful search. This therefore reduces the marginal gains of search. If we consider two individuals one who is risk loving $(A_{\hat{y}^*}^L)$ and the other who is risk averse $(A_{\hat{y}^*}^H)$, equation 8 implies that, given a job offer, risk averse worker is more critical of the job offers $(\hat{y}_H^* > \hat{y}_L^*)$, and therefore is more likely to reject a job offer. This implies a decrease in marginal gains from search:

$$\lambda E \int_{\hat{y}_{L}^{*}}^{y} [V(y) - V(y_{0})] dF(y) =$$

$$\lambda E \int_{\hat{y}_{L}^{*}}^{y} [V(y) - V(y_{0})] dF(y) + \lambda E \int_{\hat{y}_{H}^{*}}^{y} [V(y) - V(y_{0})] dF(y) >$$

$$\lambda E \int_{\hat{y}_{L}^{*}}^{y} [V(y) - V(y_{0})] dF(y)$$
(11)

Hence, risk aversion can affect job mobility through two channels: risk averse workers are less likely to invest in search because of uncertain rewards, and have lower expected gains from search as they are more likely to reject potential offers.

2.3. Discussion

The theoretical model sheds insights into the link between risk aversion and job mobility; however, it does not spell out some of the factors that are pertinent in the mobility process (van Huizen and Alessie, 2016). We discuss some of the factors that we think are relevant to the Zimbabwean context. The model assumes that job mobility is risky; however, this may not always be the case. Generally, the current job match is expected to offer more protection than the alternative match. This is because firms incur firing costs in form of statutory retrenchment packages and severance pay whenever they lay-off workers. The cost may be significant if a worker has longer tenure as it is proportionate to one's tenure. However, depending on the nature of the employment contract, there may be uncertainty in the current job. Employees on permanent contracts may be more certain about their security of employment compared to those on temporary contracts. Quitting a permanent job may not only mean forfeiting a secure job, but also the associated employment benefits which typically increase with tenure. Among this group, quitting a job may be riskier than staying. This may however not be the case for those in temporary jobs as staying may present more uncertainty compared to moving. The probability of job retention is typically low for workers on temporary contracts compared to those on permanent contracts. Our worker sample reports the nature of one's employment contract. in this study we empirically examine if risk aversion matters more for workers on a permanent contract.

Second, a worker's ability to mitigate negative effects of job mobility if a new match proves to be poor may be relevant. As such, labour market conditions may dictate the extent to which risk aversion affects job mobility. Unlike developed countries that have tight labour markets, developing countries and Zimbabwe in particular, offer little to no alternative jobs once one leaves current employment. Related to the previous point on certainty of current job is firm performance; in particular firm employment shocks may bring about uncertainty in the current job. In a tight labour market, if a firm is struggling even risk averse individuals' may leave current employment as the risk of staying may be high compared to that of moving. The 'sink or swim' relationship is however ambiguous in respect of developing countries where outside options are limited. We test for if there is a difference in effect between workers that work in firms that experienced employment shocks and those that did not.

3.0. Data and Methods

To test the empirical relation between risk preferences and job mobility we rely on the Matched Employer-Employee Panel Data for Labour Market Analysis in Zimbabwe (MEPLMAZ). MEPLMAZ is a representative data set that captures firm and worker information from Zimbabwean manufacturing sector. It captures information from both formal and informal manufacturing firms and workers, covering seven main industrial sub-sectors. The existing two waves of the survey (2015 -2016) form the basis of our analysis. Wave 1 contains simple incentivised experiments that measure a set of economic preferences central in capturing individual behaviour in economic choices. Despite the fact that economic theory abstracts away from details of economic preferences, they explicitly model preferences over certain attributes – timing, risk for instance, that are typically relevant in economic decisions. Economic preferences can be broadly classified under three main dimensions; time, risk and social

preferences (Golsteyn & Schildberg-Hörisch, 2017). Risk preferences define how much risk one is willing to take in the presence of uncertainty.

In this study, we follow the revealed preference paradigm, which infers preferences from choices based on incentivised experiments⁵. Subjects to an experiment receive a monetary reward in line with their choices. The benefits of incentivised experiments is that they allow for choices reflective of real life situations that can be observed for different individuals (Falk, Becker, Dohmen, Huffman & Sunde, 2016). Determining measures of these economic preferences therefore lays an important foundation for examining their role in explaining economic outcomes including those related to labour markets.

The MEPLMAZ elicits risk preference measures based on incentivised choice experiments. Experimental elicitation of preference measures is generally expensive to implement in representative samples compared to survey measures. In ideal situations, the experimental setup encompass a large menu of lotteries (like in the case of Holt and Laury, 2002), but this may be costly when one is faced with both time and financial constraints. To allow for choices that reflect individuals' risk attitudes in a multi-module survey, our experiment involves real monetary payoffs⁶, and the experimental design aims at minimising both time and financial costs.

The 2015 wave of the survey contains a novel set of questions that constitute the experiment. It randomly assigns subjects to either the risk or time preferences experiment. This resulted in 860 and 799 workers participating in the risk and time choice experiments respectively. For now, we focus on the risk subsample. The experimental design assigned subjects to different prized lotteries valued between US\$2 and US\$7. Subjects chose between participating in a gamble with higher stakes or abstain and get a sure but lower amount.

The experiment structured the risk elicitation task as follows:

"As a token for participating, we would like to give you some airtime credit. Either we can transfer US\$2 to your phone tomorrow or you can play a game for more money. If you win, you will get US\$X (US\$2 to \$7) but if you lose, you will get nothing. You have an equal chance of winning or losing. Which one would you like? How much money will make you want to play the game. Note: enter 999 if person does not play these types of games (e.g. for religious reasons). What amount would make you rather take the \$2 for sure?"

From the simple experiments, we gathered information on individuals' lottery choices and the associated reservation prices. We begin by summarising the "raw" data to learn how risk and time choices vary across individual respondents.

3.1.1. Risk preferences subsample

Table 1 presents the choices of the subjects. The table summarise the experimental setup by risk options offered, disaggregating between individuals who took the safe option and those who chose the gamble. The majority of the workers chose the US\$2 sure option (i.e. chose not to play the gamble) 730 (84.9%), while the rest 130 (15.1%) took the gamble.

Table 1: Summary of the risk choice options

_

⁵ Following traditions in psychology, economists have also developed non-incentivised measures that rely on self-reports in the form of a questionnaire. An example is the risk preferences measure in the German Socio Economic Panel (SOEP) data, which rates individuals preferences on a 11 point Likert scale (Dohmen, Falk, Huffman, Sunde, Schupp & Wagner, 2011b).

⁶ The monetary amounts (between US\$ 2-7) were big enough to motivate individuals to behave in a way that reveals their true risk and time preferences. The worker survey took at most 15 minutes to administer, and as such going by individuals' hourly wages (just less than US\$2) the amounts were significantly higher than one's average 15 min pay. In addition, in the time preference task, a larger proportion took higher amounts even though they came with a time delay.

Gamble Amount	Expected payoff	Number of workers	Safe option	Gamble
2	1.00	19	16 (84.2%)	3 (15.8%)
3	1.50	100	91 (91%)	9 (9%)
4	2.00	234	207 (88.5%)	27 (11.5%)
5	2.50	175	146 (83.4%)	29 (16.6%)
6	3.00	210	173 (82.4%)	37 (17.6%)
7	3.50	121	96 (79.3%)	25 (20.7%)
Total		860	730 (84.9%)	130 (15.1%)

NB: expected payoffs is the lottery price multiplied by the probability of winning (p=0.5).

Figure 1 provides a visual representation of the data in table 1. The plots further disaggregates participants' choices in the experiment as proportions. The data shows that with increasing payoffs, individuals are attracted to participate in the gamble.



Figure 1: Distribution of Gamble Choices

The survey further probes subjects about their reservation prices. Figure 2 classifies the respondents' reservation prices for those that took the gamble (plot a) and those that chose the safe option (plot b), averaged for different lottery options offered to subjects. The blue line summarises the amounts that are acceptable for one to take the gamble, and the red line represents amounts that would rather make individuals take the sure amount.

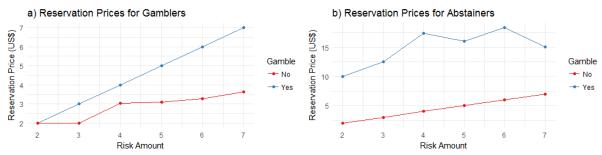


Figure 2: Workers' average reservation prices per given lottery

In plot (a) the red line (reservation prices) is the average amount that would tempt a participant to forgo a given lottery for the sure amount. For example, subjects who accepted the US\$5 gamble would only abstain from the gamble and take the sure amount (\$2) if the gamble is

reduced to an average of US\$3. The blue line in plot (b) summaries the average lottery price that would tempt participant into taking part in the gamble given initial offers highlighted by the red line. For instance, subjects who turned down a US\$5 gamble for a sure amount of US\$2 require more than double the amount (at least US\$16) to tempt them into participate in the gamble. This translates into expected values (at least US\$8) that are by far greater than the sure amount offered in the experiment (US\$2), indicating the risk averse nature of these participants. In summary, the data shows that higher amounts induce subjects to take up the lottery, while lotteries closer to the sure amount (i.e. with an expected payoff less than US\$2) tempt them to abstain from gamble (appendix 1).

3.1.2. Characteristics of individuals gamble choices

As part of descriptive statistics, we take an initial interest in understanding subjects' choices in the risk experiment. To do this, we estimate a probit model on individuals' likelihood of participating in the gamble as a function of a number of variables (socio-economic and demographic characteristics) thought to influence individuals gambling decisions. Appendix 2 is a summary table of the probit model marginal effects, the dependent variable – gamble, is binary and takes a value of one if one participated and zero otherwise. The results show that the amount of the gamble positively correlates to gamble participation. Age inversely relates to gamble participation; however, the inclusion of other variables makes the relationship statistically insignificant. With higher education, the likelihood of gamble participation increases. Other factors such as wage, sector and gender enter insignificantly into the equation. While the expectation is that gender influences gambling decisions, our model fails to provide supporting evidence. Our sample is predominantly male (81%), which could explain this.

3.2. Measuring Economic Preferences

The first question this paper aims to answer relates to the nature and distribution of risk preferences amongst a sample of Zimbabwean manufacturing sector worker. In measuring risk preferences, we make a crucial assumption that subjects take the experiment in isolation of their constraints or circumstances outside the experiment.

3.2.1. Measuring risk attitudes

The unique feature of our data that makes it easier for us to derive risk preference measures is it directly captures subjects' lottery prices as well as their reservation prices. Given the nature of our data, we use the Arrow-Pratt⁷ approximation to measure individuals' risk aversion. We follow Cramer *et al.*, (2002) and specify the measure of absolute risk aversion as below:

$$\rho = \frac{\alpha Z - \lambda}{(\lambda^2/_2 + \alpha Z^2/_2 - \alpha \lambda Z)} \tag{12}$$

Where Z is the lottery prize, α the probability of winning the lottery (0.5), and λ an individual's reservation price, or minimum amount that would tempt them to reverse their gamble choice. For individuals who participated in the gamble, the lottery price is the gamble amount offered and the participants directly report the reservation price. This however is not the case for individuals who abstained from the gamble; their lottery price is the amount that would induce

⁷ Cramer *et al.*, (2002) provides a detailed derivation of the measure of absolute risk aversion from Arrow-Pratt's (Pratt, 1964) original formulation based on the common utility functions ($\rho = \frac{-\upsilon''}{\upsilon'}$). We adopt this formulation for the purpose of our present analysis.

them to play the gamble and their reservation price is the lottery price offered in the experiment (refer to figure 2). An Arrow Pratt value $\rho < 0$ indicates risk-seeking behaviour, $\rho = 0$ signals risk neutrality and $\rho > 0$ shows risk aversion.

We use the risk preferences data to compute the Arrow-Pratt risk measure; we report a mean value of -0.109 with a standard deviation of 0.224. The data shows that an average participant exudes risk-seeking behaviour. In Figure 3, we examine the distribution of individuals risk attitudes for male and female participants disaggregated by their occupational sector using density plots. The density plots however show something interesting; most of the participants score just above zero, and as such, a few individuals who exude extremely risk-seeking behaviour might be behind the negative mean.

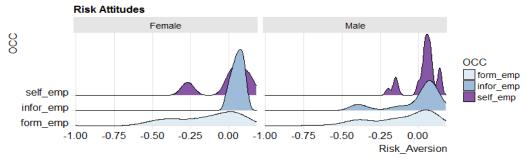


Figure 3: Distribution of individuals risk attitudes by gender and occupational sector

3.2.2. Characteristics of individuals' risk preferences

To help unpack the nature and sources of variation in individuals risk aversion, we relate our risk aversion measure to a set of individual demographic and geographic variables proposed as potential covariates of risk preferences in the empirical literature. The estimates of relationship between the Arrow-Pratt measure of risk aversion and individual demographic characteristics using ordinary least square (OLS) regressions is presented in Appendix 2. The results are simple raw correlations; however, they speak to what previous literature has articulated and hypothesised (Borghans, Heckman, Golsteyn & Meijers, 2009; Dohmen et al., 2010; Falk, Becker, Dohmen, Enke, Huffman & Sunde, 2018; Wik, Aragie Kebede, Bergland & Holden, 2004). We find that workers' risk attitudes differ by one's sector of employment, geographical location and ethnic group. On average informal sector workers are more risk averse than formal sector workers. Regarding geographical location, Bulawayo based employees are more risk loving compared to those from other regions of the country and the relationship is robust to the inclusion of an ethnic variable. The other demographic characteristics that typically correlate with risk preferences (age and gender) enter the regression equation insignificantly. Empirical results from similar economies largely report females to be more risk averse compared to males (Wik et al., 2004), we however fail to establish this in our study. The result is unsurprisingly as the sample is predominantly male. Despite literature largely reporting increasing risk aversion with age (Borghans et al., 2009; Falk et al., 2018), some studies also report an insignificant relation (Abreha, 2007; Senkondo, 2000).

3.3. Estimating employee mobility

The main empirical question this study seeks to answer is whether heterogeneity in risk aversion explains job mobility amongst a sample of Zimbabwean workers. We use the existing two waves of the survey to answer this important empirical question. The first wave contains the main variable of interest as well as covariates that feed into the regression model. The

second wave provides the job mobility variable. In the previous chapter, we estimated individuals' mobility patterns and control for personality traits; in this paper, we extend the analysis by controlling for individual risk preferences in the mobility equation. We use discrete choice models to estimate worker's probability of moving given a set of human capital and firm specific characteristics thought to explain mobility. We test the empirical relation between risk preferences and job mobility using a probit model. The estimation model is specified as follows:

$$left_firm_{it} = \delta_0 + \delta_1 R_{it} + \delta_2 X_{it} + \mu_{it}$$
(13)

Our dependent variable $left_firm_{it}$ is bivariate, and we code participants one (1) if they left firm and zero (0) if they stayed between the two waves of the survey (2015 -2016). Our main variable of interest R_{it} captures workers risk aversion. The variable X_{it} captures a set of covariates including individual and job characteristics empirically shown to explain job mobility. These variable include, age, gender, marital status, household size, education, tenure, nature of employment contract, sector of employment and employment shocks.

The empirical literature shows that risk aversion may affect individuals' occupational and sectorial choices (Bennett *et al.*, 2012; Falco, Kerr, Rankin, Sandefur & Teal, 2011; Skriabikova *et al.*, 2014). This may raise concerns that certain firm and job characteristics may be 'bad controls' in our model. Unfortunately, our data only captures workers information post labour market entry. We argue that controlling for these characteristics is important as it provides insights on the empirical relationship between risk aversion and job mobility conditional on firm and job characteristics. We therefore estimate different specification of the mobility model: initially we exclude risk preferences and estimate the basic model and include controls firm and job characteristics. We then control for risk aversion (R_{it}), and incrementally add controls for firm and job characteristic in subsequent models (X_{it}).

4.0. Empirical results

The section examines the empirical relationship between risk aversion and labour market outcomes related to employee mobility. This study follows a new strand of literature which models risk aversion as a determinant of job mobility (Argaw *et al.*, 2017; van Huizen & Alessie, 2016). Our conceptual framework (Section 2.2.) postulates that risk averse individuals are less likely to experience job mobility compared to those that are risk tolerant. We argue that risk aversion potentially affects job changing behaviours through two channels: job search and job acceptance. To empirically test the hypothesised relationship we estimate probit models using the specification provided in Equation 13. The 2015 wave of the survey captures the covariates (including risk aversion) which we use to estimate the probability of job mobility in 2016.

4.1. Risk Preferences and Mobility Patterns

Table 2 presents the main findings. Using the risk preferences sub sample (N=860) we begin the analysis by estimating the basic mobility model (column 1 and 2). In these columns, we control for the traditional variables including job and firm characteristics empirically known to influence mobility. Subsequent columns control for risk preferences, incrementally adding controls for firm and job characteristics. We can interpret the results presented in Table 2 as the marginal effects on the probability of experiencing job mobility for each covariates as specified in the model. As defined previously the dependent variable is binary and takes a value of one if worker has moved from their previous job and zero otherwise.

Table 2: Effects of risk aversion on employee mobility

Left firm (yes =1)	1	2	3	4	5	6	7
Risk_Ave			-0.223***	-0.210**	-0.164**	-0.207**	-0.155
			(0.084)	(0.083)	(0.082)	(0.100)	(0.161)
age	-0.005	-0.006		-0.019*	-0.007	0.003	0.003
	(0.010)	(0.008)		(0.011)	(0.012)	(0.017)	(0.017)
agesqr	0.093	0.094		0.240^{*}	0.127	0.039	0.045
	(0.111)	(0.089)		(0.126)	(0.137)	(0.186)	(0.186)
male	-0.069	-0.026		-0.092	-0.079	-0.104	-0.100
	(0.049)	(0.038)		(0.062)	(0.061)	(0.081)	(0.081)
married	-0.092	-0.085			0.009	-0.003	-0.007
	(0.062)	(0.052)			(0.060)	(0.079)	(0.081)
yrs_educ	-0.002	-0.003			-0.002	-0.005	-0.005
	(0.008)	(0.006)			(0.010)	(0.012)	(0.012)
hhsize	0.013	0.013^{*}			0.006	0.005	0.005
	(0.008)	(0.007)			(0.010)	(0.013)	(0.013)
log_tenure	-0.082***	-0.040**			-0.058**	-0.133***	-0.131***
	(0.021)	(0.017)			(0.026)	(0.036)	(0.036)
shock	0.117^{***}					0.154^{***}	0.139^{**}
	(0.035)					(0.057)	(0.068)
informal		-0.139***			-0.136***		
		(0.024)			(0.038)		
permanent						-0.027	-0.029
						(0.066)	(0.066)
Risk_Ave:shock							-0.085
							(0.211)
Num. obs.	485	653	313	313	311	230	230
Log Likelihood	-201.757	-266.570	-135.591	-132.539	-125.501	-96.006	-95.925
Deviance	403.514	533.140	271.182	265.079	251.003	194.011	193.850
AIC	421.514	551.140	275.182	275.079	271.003	216.011	217.850
BIC	459.171	591.474	282.674	293.810	308.400	257.268	262.546

***p < 0.01, **p < 0.05, *p < 0.1

The basic mobility equation excluding risk measures (column 1 and 2) shows that worker's household size, tenure, sector of employment and employment level shocks explains external job mobility. The results show that the main demographic characteristics (age, gender, marital status) except for household size fail to explain mobility. Workers from large sized households are more likely to move from their jobs. Workers with longer tenure are less likely to move compared to those with short tenure. Following the search and match literature, the results imply that these individuals are more likely to have evaluated and concluded that their current job provides the best match quality. As such, quitting a job may mean forfeiting a secure job and employment benefits. In an environment of constrained outside alternatives this may be costly. On the other hand, firms may be reluctant to fire their long serving workers, mainly because of the costs associated with such. These could be terminal benefits (which increase with tenure), institutional memory and accumulated firm specific human capital (training). Interestingly we find that job mobility is more common in the formal sector compared to the informal sector. The results are a reflection of the increasing significance of the informal sector as a source of employment in the face of massive contraction of formal manufacturing activities in Zimbabwe.

In the subsequent columns (3 through to 7), we address the main research question by controlling for individuals risk preferences using the computed Arrow Pratt risk aversion measure. Our result is in line with our theoretical prediction, supporting the proposition that risk averse workers are less likely than risk tolerant workers to experience job mobility. A unit increases in risk aversion is associated with roughly a 20% decrease in the probability of mobility holding everything else constant. To check if our results are sensitive to different specifications, we add controls for individual and job characteristics in subsequent specifications (column 4 to 7). Interestingly, age and its square become significant in column 4, however the weak relationship (an inverted one) varnishes as we add controls for other human and job characteristics that typically explain job mobility. In column 5 to 6, we control for tenure, sector of employment and employment shocks. Our main variable of interest remains statistically significant and returns the hypothesised relationship. To this end, our results find empirical support from recent studies on the effects of risk aversion on job mobility (Argaw et al., 2017; van Huizen & Alessie, 2016; Vardaman et al., 2008). Job mobility is inherently risky; it can potentially result in a bad match, loss of earnings and employment benefits and in the case of Zimbabwe long-term unemployment.

In section 2.3, we argue that labour market conditions may moderate the effects of risk aversion on worker's mobility decisions. In particular, it may be risky to leave a stable job in a firm that is doing well, than it is to leave a sinking ship. We test this hypothesis in column 7, by interacting risk aversion and employment shocks. Our results show that that there are no interaction effects between risk aversion and employment shocks on job mobility; both the interaction term and the risk aversion variable become insignificant. The employment shock variable however remains statistically significant. Interestingly, the results return the same direction of relationship, and the coefficient (risk aversion plus interaction term) is almost similar to the one reported in column 3. One explanation could be that the interaction term may have restricted the number of observations between the categories of movers and stayers.

4.2. Binary choice fixed effects model on risk preferences and job mobility

Information from the Zimbabwe national budget (2015) shows differences in capacity utilisation by industrial sectors, with the food and beverages sector for instance reporting the highest level of capacity utilisation (GoZ, 2015). As part of robustness checks, we control for the role of unobservable industrial sector characteristics, which may affect worker's mobility decisions. We argue that workers' industrial sector could potentially hide important information that may help us understand the effects of risk aversion on the observed patterns of job mobility. To address this we estimate industry fixed effects models for the risk subsamples using the *bife()* package in R (Stammann, Heiß & McFadden, 2016). The survey collects data from seven industrial sub-sectors, and we use industrial sub-sector as the unit for our fixed effects. We present the probit fixed effects model parameters in the appendices (Appendix 4). For easy of interpretation, in Table 3 we present the model average partial effects computed using *apeff_bife()* an inbuilt function of *bife* package in R.

Table 3: Probit Model Average Partial Effects on Risk Preferences and Mobility

Left job (1= yes)	APE	APEC
Risk aversion	-0.168*	-0.168 [*]
age	-0.025	-0.025
agesqr/100	0.332^{*}	0.332^{*}
male	-0.102*	-0.102*
married	-0.006	-0.006

yrs_educ	-0.047	-0.047
educsqr	0.002	0.002
hhsize	0.006	0.006
tenure	-0.008**	-0.008**
Shock	0.191^{***}	0.191^{***}

 $^{***}p < 0.01, \, ^{**}p < 0.05, \, ^{*}p < 0.1$

Note: APE is the usual uncorrected average partial effects; APEC is the semi-corrected average partial effects (corrected for analytical bias). Average partial effects are sometimes referred to as marginal effects (Stammann et al., 2016).

The results confirm the main empirical predictions; risk averse workers are less likely to move compared to their risk tolerant pears. The result is robust to the inclusion of industry fixed effects, indicating that workers' behavioural attributes play an important role in shaping mobility decisions. Interestingly, the fixed effects model reveals that male workers are less likely to move compared to their female peers. The other variables reported as significant in Table 2, also return the same relationship.

4.3. Individual and job characteristics as moderators of mobility

So far, we have modelled the empirical relation between risk aversion and job mobility using the base model. However, in addition to the main relationship, it is possible that certain circumstances will alter the strength of the relationship. The effect of risk aversion is likely to be stronger among employees: a) on permanent contracts compared to those on temporary contracts b) in formal employment c) had on the job training. To test these hypotheses, we interact risk aversion with dummies on employment contract, sector of employment and on the job training. Appendix 3 presents the probit model average marginal effects of risk aversion estimated on workers in different employment sectors and on different employment contracts. Our interaction effects are insignificant; the results suggests no evidence of heterogeneity in effect arising from different sectors of employment, employment shocks or different employment contracts. This is also true for interaction terms that control for gender and marital status.

In addition to this, as part of additional robustness checks, we define a candidate proxy of risk attitude based on gamble participation; we group workers who took part in the gamble as risk tolerant and those who abstained as risk averse. We use this proxy variable to estimate job mobility. The variable is insignificant across all specifications. The result is unsurprising and suggests that this is a rather crude measure of individuals risk aversion, and as such, fails to capture individuals risk attitudes.

4.4. Risk aversion and nature of mobility

Following the discussion in the conceptual framework, it is important to investigate whether risk attitudes gravitate individuals towards voluntary or involuntary job mobility. Our data set contains subjects' reasons for job changes. To address the question of nature of mobility, we group the reasons into three main categories: voluntary mobility, involuntary mobility and closed firms. This variable restricts our analysis to individuals working in firms that report job mobility. Doing so guarantees that we are comparing individuals who are likely to have made job mobility decisions whilst in similar work environments. We model the job mobility process as a multinomial logit model comprising of four categories: stay (base outcome), voluntary mobility, retrenched and firm closed.

Appendix 5 is a summary table of the multinomial logit estimates for three different specifications. We control for sector of employment, employment shocks and in the last model, we interact shocks with risk aversion in the models. Our estimation results report a negative relationship between risk aversion and mobility; however, the coefficients are mostly insignificant. There are fewer observations per each category, which could possibly explain the insignificant result.

4.5.Risk aversion, job mobility and wage growth

In the empirical literature, job mobility has important implications on individuals' labour market success, as it relates to changes in incomes (Fuller, 2008; Neumark, 2002; Pavlopoulos *et al.*, 2014; Topel & Ward, 1992). On the basis of the empirical results confirming a relationship between risk aversion and mobility, we follow Skriabikova, Argaw and Maier (2017) and model the effects of risk aversion on wage changes given job mobility. We argue in the conceptual framework that risk averse individuals demand higher wages as compensation for the uncertainty associated with outside jobs. It is thus most likely that wage changes from changing jobs may differ depending on one's level of risk aversion. To address this issue we empirically model wage growth between 2015 and 2016 as a function of worker risk aversion and job changes. We specify our estimation model as follows:

$$\Delta W_{t1} = \delta_0 + \delta_1 R_{t0} + \delta_2 left_{t1} + \mu_{t1} \tag{14}$$

Where ΔW_{t1} is the change in wages between 2016 and 2015. We do not express this variable in natural logarithms as some of the workers witness negative wage changes. The other variables R_{t0} and $left_{t1}$ represent a worker's risk aversion and a dummy if the worker left job or not.

Appendix 6 reports the OLS regression results on the effects of job mobility and risk aversion on wage changes. In column, we fail to find statistical evidence to support the hypothesis that job mobility and risk aversion have an effect on wage changes. Furthermore, an interaction term that captures the effect of risk aversion on wage changes through job changes is insignificant. In column 2, we examine whether the nature of job change may affect wage changes. We restrict our analysis to individuals that experienced job mobility and split them between voluntary and involuntary job changes. We expect individuals who voluntarily move to be motivated by a better job offer than current job offer, an argument put forward by theoretical models on job mobility. We fail to find statistical evidence to support this; in fact, our sample size collapses such that it is econometrically infeasible to make analysis.

4.6. Discussion of findings

With a few exceptions (van Huizen & Alessie, 2016; Vardaman *et al.*, 2008) empirical literature on job mobility has focused on individual and job characteristics to investigate the job mobility. To some extent the inclusion of job characteristics (Hwang *et al.*, 1998; Pavlopoulos *et al.*, 2014) increased our understanding of the reasons why workers move from one job to the other, or exit from the labour markets. However, there are further important sources of job mobility that are typically not directly observable. In particular, in this study we extent the analysis by Sullivan (2014) and incorporate risk preferences in our model following (Argaw *et al.*, 2017; Vardaman *et al.*, 2008). Our study finds empirical support from previous literature and confirm the hypothesised inverse relation between risk aversion and job mobility. The study shows that worker heterogeneity in risk preferences plays an important role in explaining mobility patterns and this is robust to controls for demographic and job characteristics. Studies seeking to investigate differences in individual's economic outcomes

can profit from taking into account heterogeneity in economic preferences over and above the traditional variables proposed by economic theory.

One issue might be of concern regarding our results; reverse casualty may bias the estimated coefficient of risk aversion. Individuals may change their risk attitudes because of their labour market experiences. This may be particularly true for our survey participants who were interviewed after entering the labour markets. Some of the workers had experienced job changes before; we therefore fail to capture any possible changes in risk attitudes that could have happened before the survey that could include a reversed casual direction of job changes affecting attitudes towards risk. Previous studies investigating the effects of risk preferences on job mobility however find no evidence of such reverse casualty (Argaw *et al.*, 2017). In addition, a new strand of literature examining the stability of risk preferences has not yet produced compelling evidence that shows systematic changes risk preferences in adulthood (Falk *et al.*, 2018).

As an extension to the main objectives of the study, we follow Skriabikova, Argaw and Maier (2017) and put to test the hypothesis that risk aversion may affect the effect of job mobility on wage growth. We fail to find evidence to support this in the Zimbabwean manufacturing sample. We cannot however conclude that risk aversion has no effect on wage growth. Future studies could expand on these findings and use a larger sample to track the wage effects of job changes accounting for individuals risk attitudes.

5.0. Conclusion

Employee mobility is an inevitable phenomenon and characteristic of modern labour markets. Theoretical models that predict job changes concentrate on observable individual and job characteristics (Burdett, 1978; Jovanovic, 1979) and assume neutrality of risk preferences. However changing jobs is inherently risk, partly because of search and information frictions, thus worker's risk attitudes play a part when deciding whether to move or stay. In this study, we build on the work of van Huizen and Alessie (2016) and address theoretically and examine empirically the effects of risk aversion on job mobility. We adopt a model in which risk preferences can potentially affect job mobility decisions through two channels; job search and reservation match. The study contributes to the recent literature on the effects of risk preferences on job mobility by extending the analysis to a developing country characterised by uncertainty. We exploit a unique employer-employee data set, the "Matched Employee Panel Data for Labour Market Analysis in Zimbabwe" (MEPLMAZ) that contains experimentally elicited measures of risk preferences to investigate the external movement of employees between two waves of a survey.

Allowing for heterogeneity in economic preferences, we demonstrate that risk aversion explain employee mobility. The results are consistent with earlier findings and confirm the theoretical predictions of van Huizen and Alessie (2016). The study has important implications on the employment dynamics in an environment characterised by economic uncertainty, in particular how individuals' behaviour influence decisions making. These findings are an important basis towards tapping the potential of the MEPLMAZ data. The data are well suited for many potential agendas on the effects of variations in risk preferences on labour market outcomes. One example is the combined effect of risk preferences and personality traits on employment outcomes related to sectoral selection, earnings and job mobility. In particular, it may be interesting to see if personality traits moderate the effect of risk preferences on individuals' life

outcomes. In summary, attitudes towards risk significantly explain individuals' mobility patterns in developing country labour markets characterised by uncertainty.

Reference

- Ahn, T. 2010. Attitudes toward risk and self-employment of young workers. *Labour Economics*. 17(2):434–442.
- Argaw, B.A., Maier, M.F. & Skriabikova, O.J. 2017. Risk Attitudes, Job Mobility and Subsequent Wage Growth During the Early Career. *ZEW Discussion Papers*. 17(023). [Online], Available: http://hdl.handle.net/10419/161630%0A.
- Baird, M.D. 2017. Labor Supply Estimation Biases From Disregarding Nonwage Benefits. *Economic Inquiry*. 55(2):1064–1090.
- Basbug, G. & Sharone, O. 2017. The Emotional Toll of Long-Term Unemployment: Examining the Interaction Effects of Gender and Marital Status. *The Russell Sage Foundation Journal of the Social Sciences*. 3(3):222.
- Bennett, J., Gould, M. & Rablen, M.D. 2012. Risk attitudes and informal employment in a developing economy. *IZA Journal of Labor & Development*. 1(1):5.
- van den Berg, M., Fort, R. & Burger, K. 2009. Natural Hazards And Risk Aversion: Experimental Evidence From Latin America. *Conference of the International Association of Agricultural Economists*.
- Bonhomme, S., Jolivet, G. & Leuven, E. 2016. School Characteristics and Teacher Turnover: Assessing the Role of Preferences and Opportunities. *Economic Journal*. 126(594):1342–1371.
- Bonin, H., Dohmen, T., Falk, A., Huffman, D. & Sunde, U. 2007. Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. *Labour Economics*. 14(6):926–937.
- Borghans, L., Heckman, J.J., Golsteyn, B.H.H. & Meijers, H. 2009. Gender Differences in Risk Aversion. *Journal of the European Economic Association*. 7(2–3):649–658.
- Burdett, K. 1978. A Theory of Employee Job Search and Quit Rates. *The American Economic Review*. 68(1):212–220. [Online], Available: https://www.jstor.org/stable/1809701.
- Caliendo, M., Fossen, Æ.F.M., Kritikos, Æ.A.S., M, L.Á. & Á, D.Á.J. 2009. Risk attitudes of nascent entrepreneurs new evidence from an experimentally validated survey. 153–167.
- Camerer, C.F. & Hogarth, R.M. 1999. The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework. *Journal of Risk and Uncertainty*. 19(1–3):7–42.
- Cardenas, J.C. & Carpenter, J. 2013. Risk attitudes and economic well-being in Latin America. *Journal of Development Economics*. 103(1):52–61.
- Cho, I.S. 2012. Four essays on risk preferences, entrepreneurship, earnings, occupations, and gender.

- Cramer, J.S., Hartog, J., Jonker, N. & Van Praag, C.M. 2002. Low risk aversion encourages the choice for entrepreneurship: An empirical test of a truism. *Journal of Economic Behavior and Organization*. 48(1):29–36.
- Dohmen, T., Falk, A., Huffman, D. & Sunde, U. 2010. Are Risk Aversion and Impatience Related to Cognitive Ability? Vol. 100.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. & Wagner, G.G. 2011a. Individual Risk Attitude: Measurement, Determinants, and Behavioral Consequences. *Journal of the European Economic Association*. 9(3):522–550.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. & Wagner, G.G. 2011b. Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*. 9(3):522–550.
- Dohmen, T., Lehmann, H. & Pignatti, N. 2016. Time-varying individual risk attitudes over the Great Recession: A comparison of Germany and Ukraine. *Journal of Comparative Economics*. 44(1):182–200.
- Ekelund, J., Johansson, E., Järvelin, M.R. & Lichtermann, D. 2005. Self-employment and risk aversion Evidence from psychological test data. *Labour Economics*. 12(5):649–659.
- Falco, P. 2014. Does risk matter for occupational choices? Experimental evidence from an African labour market. *Labour Economics*. 28:96–109.
- Falco, P., Kerr, A., Rankin, N., Sandefur, J. & Teal, F. 2011. The returns to formality and informality in urban Africa ★. *Labour Economics*. 18:S23–S31.
- Falk, A., Becker, A., Dohmen, T., Huffman, D. & Sunde, U. 2016. The Preference Survey Module: A Validated Instrument for Measuring Risk, Time and Social Preferences. *IZA Discussion Paper*. (9674).
- Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D. & Sunde, U. 2018. Global Evidence on Economic Preferences. *The Quarterly Journal of Economics*. 133(4):1645–1692.
- Fouarge, D., Kriechel, B. & Dohmen, T. 2014. Occupational sorting of school graduates: The role of economic preferences. *Journal of Economic Behavior and Organization*. 106:335–351.
- Fuller, S. 2008. Job mobility and wage trajectories for men and women in the United States. *American Sociological Review*. 73(1):158–183.
- Golsteyn, B. & Schildberg-Hörisch, H. 2017. Challenges in Research on Preferences and Personality Traits: Measurement, Stability, and Inference Challenges. *IZA Discussion Paper Series*. (10562).
- Holt, C.A. & Laury, S.K. 2002. Risk aversion and incentive effects. *American Economic Review*. 92(5):1644–1655.
- Holt, C.A. & Laury, S.K. 2014. Assessment and estimation of risk preferences. Vol. 1. Elsevier B.V.

- Huizen, T. Van. n.d. Risk Aversion and Turnover. (October 2013).
- van Huizen, T. & Alessie, R. 2016. Risk Aversion and Job Mobility. U.S.E. Discussion Paper Series. 16(09).
- Hwang, H., Mortensen, D.T. & Reed, W.R. 1998. Hedonic Wages and Labor Market Search. *Journal of Labor Economics*. 16(4):815–847.
- Johnson, W.R.. 1978. A Theory of Job Shopping. *The Quarterly Journal of Economics*. 92(2):261–278. [Online], Available: https://www.jstor.org/stable/1884162.
- Jovanovic, B. 1979. Job Matching and the Theory of Turnover. *Journal of Political Economy*. 87(5):972–990. [Online], Available: https://www.jstor.org/stable/1833078.
- Kahneman, D. & Tversky, A. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica*. 47(2):263–291.
- Kim, Y.-I. & Lee, J. 2012. Estimating Risk Aversion Using Individual-Level Survey Data: Implications for High Self-Employment Ratio in South Korea. *The Korean Economic Review*. 28(2):221–239.
- Le, A.T., Miller, P.W., Slutske, W.S. & Martin, N.G. 2014. Attitudes toward economic risk and occupational choice. *Industrial Relations*. 53(4):568–592.
- Lönnqvist, J.E., Verkasalo, M., Walkowitz, G. & Wichardt, P.C. 2015. Measuring individual risk attitudes in the lab: Task or ask? An empirical comparison. *Journal of Economic Behavior and Organization*. 119:254–266.
- Miller, P.W., Slutske, W.S., Martin, N.G. & Le, A.T. 2010. Attitudes towards Economic Risk and the Gender Pay Gap. *Labour Economics*. 18(4):555–561.
- Mortensen, B.D.T. 2011. Markets with Search Friction and the DMP Model. *American Economic Review*. 101(June):1073–1091.
- Neumark, D. 2002. Youth Labor Markets in the United States: Shopping around vs. Staying Put. *The Review of Economics and Statistics*. 84(3):462–482. [Online], Available: https://www.jstor.org/stable/3211564.
- Pavlopoulos, D., Fouarge, D., Muffels, R. & Vermunt, J.K. 2014. Who Benefits from a Job Change: The dwarfs or the giants? *European Societies*. 16(2):299–319.
- Pfeifer, C. 2010. Risk Aversion and Sorting into Public Sector Employment. *German Economic Review*. 12(1):85–99.
- Skriabikova, O.J., Dohmen, T. & Kriechel, B. 2014. New evidence on the relationship between risk attitudes and self-employment. *Labour Economics*. 30:176–184.
- Stammann, A., Heiß, F. & McFadden, D. 2016. Estimating Fixed Effects Logit Models with Large Panel. (Working Paper).
- Sullivan, P. & To, T. 2014. Search and Nonwage Job Characteristics. *Journal of Human Resources*. 49(2):472–507.

- Thomas, P.J. 2016. Measuring risk-aversion: The challenge. *Measurement: Journal of the International Measurement Confederation*. 79:285–301.
- Topel, R.H. & Ward, M.P. 1992. Job Mobility and the Careers of Young Men. *The Quarterly Journal of Economics*. 107(2):439–479. [Online], Available: https://www.jstor.org/stable/2118478.
- Vardaman, J.M., Allen, D.G., Renn, R.W. & Moffitt, K.R. 2008. Should I stay or should I go? The role of risk in employee turnover decisions. *Human Relations*. 61(11):1531–1563.
- Wik, M., Aragie Kebede, T., Bergland, O. & Holden, S.T. 2004. On the measurement of risk aversion from experimental data. *Applied Economics*. 36(21):2443–2451.
- ZIMSTAT. 2015. 2014 Labour Force Survey.

Appendices
Appendix 1: Probit model on choice of Gamble

Probit model on risk choice: Dependent variable is gamble (1 = gamble)

Gamble $(1 = yes)$	1	2	3	4	5
Risk_Amount	0.006	0.042**	0.025***	0.025***	0.024***
	(0.069)	(0.021)	(0.009)	(0.009)	(0.009)
I(Risk_Amount^2)	0.002				
	(0.007)				
age	-0.003**	-0.002	-0.001	-0.002	-0.003
	(0.001)	(0.001)	(0.007)	(0.007)	(0.007)
male		0.074	-0.025	-0.026	-0.028
		(0.096)	(0.032)	(0.033)	(0.033)
married		-0.068*	-0.056	-0.046	-0.046
		(0.038)	(0.040)	(0.040)	(0.040)
Risk Amount:male		-0.022			
		(0.023)			
agesqr			0.007	0.019	0.033
			(0.081)	(0.081)	(0.082)
yrs_educ			0.019***	0.016***	0.015^{**}
			(0.006)	(0.006)	(0.006)
informal			-0.021	-0.030	
			(0.032)	(0.033)	
log_wage				0.011	0.012
				(0.018)	(0.018)
Informal employment					-0.060
					(0.038)
Self-employment					0.006
					(0.051)
Num. obs.	859	859	859	814	814
Log Likelihood	-358.073	-354.792	-348.158	-325.064	-324.461
Deviance	716.147	709.584	696.316	650.128	648.922
AIC	724.147	721.584	712.316	668.128	668.922
BIC	743.170	750.118	750.362	710.446	715.942

Appendix 2: Risk Attitudes and Individual Specific Characteristics

1	2	3	1	5	6
<u> </u>					
-0.002	-0.006	-0.004	-0.007	-0.007	-0.009
(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
0.014	0.055	0.047	0.085	0.086	0.111
(0.068)	(0.076)	(0.075)	(0.075)	(0.075)	(0.076)
0.035	0.024	0.019	0.009	-0.001	-0.002
(0.029)	(0.029)	(0.029)	(0.028)	(0.029)	(0.029)
	0.053	0.051	0.047	0.041	0.044
	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)
	-0.003	0.002	0.000	0.002	0.002
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
		0.142***	0.149^{***}	0.132***	0.145***
		(0.030)	(0.031)	(0.031)	(0.031)
			-0.087***		-0.065**
	0.014 (0.068) 0.035	(0.006) (0.007) 0.014 0.055 (0.068) (0.076) 0.035 0.024 (0.029) (0.029) 0.053 (0.033) -0.003	-0.002 -0.006 -0.004 (0.006) (0.007) (0.006) 0.014 0.055 0.047 (0.068) (0.076) (0.075) 0.035 0.024 0.019 (0.029) (0.029) (0.029) 0.053 0.051 (0.033) (0.032) -0.003 0.002 (0.006) (0.005) 0.142****	-0.002 -0.006 -0.004 -0.007 (0.006) (0.007) (0.006) (0.006) 0.014 0.055 0.047 0.085 (0.068) (0.076) (0.075) (0.075) 0.035 0.024 0.019 0.009 (0.029) (0.029) (0.029) (0.028) 0.053 0.051 0.047 (0.033) (0.032) (0.032) -0.003 0.002 0.000 (0.006) (0.005) (0.005) 0.142*** 0.149*** (0.030) (0.031)	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

23

				(0.026)		(0.030)
Gweru				-0.024		-0.043
				(0.047)		(0.051)
Mutare				0.036		0.057
				(0.048)		(0.051)
Ndebele					-0.109***	-0.067^*
					(0.033)	(0.038)
Karanga					-0.027	-0.036
					(0.031)	(0.033)
Manyika					0.007	0.028
					(0.029)	(0.031)
Foreigner					0.058	0.053
					(0.155)	(0.154)
\mathbb{R}^2	0.005	0.014	0.066	0.095	0.096	0.112
Adj. R ²	-0.002	0.001	0.051	0.074	0.073	0.082
Num. obs.	398	398	398	398	398	398
RMSE	0.224	0.223	0.218	0.215	0.215	0.214

^{***}p < 0.01, **p < 0.05, *p < 0.1

Appendix 3: Risk Preferences and Employee Mobility: Interactions

Left job (1=yes)	1	2	3	4	5	6	7
Risk_Ave	0.085	-0.203	-0.350	-0.162**	-0.211	-0.183**	-0.121
	(0.309)	(0.201)	(0.399)	(0.080)	(0.152)	(0.093)	(0.184)
age	-0.006	-0.005	-0.005	-0.005	-0.005	-0.006	-0.005
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)
agesqr	0.105	0.107	0.109	0.103	0.109	0.121	0.105
	(0.142)	(0.142)	(0.142)	(0.136)	(0.142)	(0.155)	(0.141)
male	-0.077	-0.077	-0.076	-0.074	-0.076	-0.098	-0.087
	(0.062)	(0.062)	(0.062)	(0.060)	(0.062)	(0.070)	(0.075)
married	0.008	0.016	0.008	0.007	0.008	0.019	0.008
	(0.062)	(0.071)	(0.062)	(0.060)	(0.062)	(0.067)	(0.061)
yrs_educ	-0.001	-0.001	0.003	-0.001	-0.001	0.001	-0.001
	(0.010)	(0.010)	(0.012)	(0.009)	(0.010)	(0.011)	(0.010)
hhsize	0.007	0.006	0.006	0.006	0.006	0.006	0.006
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
log_tenure	-0.054**	-0.054**	-0.054**	-0.053**	-0.054**	-0.061**	-0.054**
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.030)	(0.027)
informal	-0.146***	-0.144***	-0.143***	-0.175***	-0.141***	-0.100	-0.145***
	(0.036)	(0.037)	(0.037)	(0.037)	(0.040)	(0.071)	(0.037)
permanent	-0.033	-0.033	-0.034	-0.031	-0.022	-0.021	-0.034
	(0.052)	(0.052)	(0.052)	(0.050)	(0.061)	(0.057)	(0.053)
age:Risk_Ave	-0.006						
	(0.007)						
married:Risk_Ave		0.045					
		(0.220)					
yrs_educ:Risk_Ave			0.016				
			(0.034)				

informal:Risk_Ave				1.994			
				(2.162)			
permanent:Risk_Ave					0.065		
					(0.181)		
training						-0.094	
						(0.057)	
Risk_Ave:training						0.239	
						(0.420)	
male:Risk_Ave							-0.054
							(0.204)
Num. obs.	308	308	308	308	308	284	308
Log Likelihood	-124.463	-124.794	-124.703	-124.344	-124.750	-121.711	-124.779
Deviance	248.926	249.588	249.405	248.688	249.499	243.421	249.559
AIC	272.926	273.588	273.405	272.688	273.499	269.421	273.559
BIC	317.687	318.349	318.167	317.450	318.261	316.858	318.320
allaharia a a a a a a a a a a a a a a a a a a	ata and a second						

^{***}p < 0.01, **p < 0.05, *p < 0.1

Appendix 4: Fixed effects probit model with analytical bias-correction

Fixed effects probit model with analytical bias-correction

```
Estimated model:
```

```
left_job ~ age + agesqr + male + married + yrs_educ + educsqr +
   hhsize + tenure + Risk_Ave + shock | indu_sector
```

```
Log-Likelihood= -94.3855
n= 228, number of events= 44
```

Demeaning converged after 5 iteration(s)
Offset converged after 4 iteration(s)

Corrected structural parameter(s):

```
Estimate Std. error t-value Pr(> t)
                      0.069297
                                 -1.511 0.13234
         -0.104689
age
         1.393500
-0.537151
                      0.795044
0.276818
                                 1.753 0.08109
-1.940 0.05365
agesqr
male
married
         -0.021317
                      0.328067
                                 -0.065 0.94825
yrs_educ
         0.196528
                      0.297302
                                  0.661 0.50931
         -0.009398
                      0.012180
educsgr
                                 -0.772 0.44123
          0.022649
                      0.052546
                                  0.431 0.66688
hhsize
         -0.035380
                      0.014071
                                 -2.514 0.01267 *
tenure
Risk_Ave -0.705776
                      0.416341
                                 -1.695 0.09151
                                 2.847 0.00484 **
          0.655768
shock
                      0.230312
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

AIC= 220.7709 , BIC= 275.6404

(632 observation(s) deleted due to missingness) Average individual fixed effects= 0.1558

Appendix 5: Estimated Multinomial Logit Coefficients on Risk and Nature of Job Mobility.

		(1)			(2)			(3)	
Left job (1=stay)	voluntary	retrench	closed	voluntary	retrench	closed	voluntary	retrench	closed
Risk_Ave	-1.214	-0.385	-2.277*	-1.150	-0.001	-1.717*	0.107	0.388	-5.502
	(1.355)	(1.106)	(1.170)	(1.289)	(0.994)	(1.003)	(2.205)	(1.577)	(3.933)
age	-0.344	0.095	0.212	-0.250	-0.004	0.237	-0.333	0.094	0.206
	(0.252)	(0.160)	(0.289)	(0.218)	(0.141)	(0.215)	(0.249)	(0.160)	(0.282)
agesqr	4.689	-0.448	-1.467	3.243	0.501	-2.206	4.509	-0.437	-1.397
	(2.981)	(1.795)	(3.178)	(2.636)	(1.574)	(2.406)	(2.942)	(1.789)	(3.068)
male	-1.894**	-1.337**	0.263	-1.606**	-0.864	0.791	-1.747*	-1.253*	0.108
	(0.892)	(0.654)	(1.364)	(0.755)	(0.594)	(1.142)	(0.901)	(0.665)	(1.343)
married	-0.570	-0.167	0.797	-0.534	-0.016	0.505	-0.752	-0.279	1.050
	(1.126)	(0.866)	(1.626)	(1.006)	(0.828)	(1.083)	(1.161)	(0.880)	(1.660)
yrs_educ	3.362^{*}	0.237	0.576	2.062	-0.007	-0.130	3.176	0.270	0.560
	(2.007)	(0.569)	(0.990)	(1.705)	(0.490)	(0.549)	(1.947)	(0.563)	(1.018)
educsqr	-0.126	-0.012	-0.025	-0.078	-0.001	0.006	-0.120	-0.013	-0.023
	(0.077)	(0.024)	(0.044)	(0.065)	(0.021)	(0.025)	(0.075)	(0.024)	(0.045)
hhsize	0.304^{*}	0.042	-0.431	0.268^{*}	0.092	-0.349*	0.287^{*}	0.044	-0.485*
	(0.157)	(0.143)	(0.268)	(0.153)	(0.124)	(0.198)	(0.155)	(0.141)	(0.287)
tenure	-0.069	-0.097**	-0.054	-0.033	-0.046	0.004	-0.061	-0.094**	-0.056
	(0.055)	(0.040)	(0.043)	(0.050)	(0.029)	(0.033)	(0.056)	(0.041)	(0.042)
shock	1.243*	0.635	3.468***				0.749	0.362	4.739**
	(0.732)	(0.591)	(1.146)				(0.963)	(0.709)	(2.228)
informal				3.389**	-12.324***	-12.284***			
				(1.691)	(0.000)	(0.000)			
shock:Risk_Ave							-2.373	-1.659	3.188
							(2.940)	(2.271)	(4.116)
AIC	275.585	275.585	275.585	336.048	336.048	336.048	279.642	279.642	279.642
BIC	371.459	371.459	371.459	436.904	436.904	436.904	384.232	384.232	384.232
Log Likelihood	-104.792	-104.792	-104.792	-135.024	-135.024	-135.024	-103.821	-103.821	-103.821
Deviance	209.585	209.585	209.585	270.048	270.048	270.048	207.642	207.642	207.642
Num. obs.	135	135	135	157	157	157	135	135	135

^{***}p < 0.01, **p < 0.05, *p < 0.1

Appendix 6: Wage changes, risk aversion and job mobility

1	2
-4.318	-5.644
(13.068)	(69.747)
-32.635	
(56.363)	
44.318	-79.621
(53.805)	(143.809)
-175.365	
(138.120)	
	-120.274
	(128.516)
	-366.963
	(420.882)
0.007	0.185
-0.005	-0.087
235	13
173.045	182.709
	-4.318 (13.068) -32.635 (56.363) 44.318 (53.805) -175.365 (138.120) 0.007 -0.005 235

^{***}p < 0.01, **p < 0.05, *p < 0.1