Applied Economics Journal Vol. 29 No. 1 (June 2022): 1-25

ISSN: 2586-9124 (PRINT)
ISSN: 2586-9132 (ONLINE)

Received: 10 May 2021
Received in revised form: 26 July 2021
Accepted: 9 August 2021

Effect of Locus of Control on Job Performance: Evidence from Australian Panel Data

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Abstract

This paper aims to examine the importance of locus of control for job performance. We draw on Australian panel data and use the fixed effects panel data analysis technique to estimate the causal effect of locus of control on working people's job performance. Our findings reveal that locus of control positively affects the adaptive performance dimension of job performance. Employees with a more internal locus of control tend to be better able to adapt to conditions and events in the workplace, leading to better performance on their jobs.

Keywords: job performance, locus of control, fixed effects model, HILDA
JEL Classification: D90, D91, J01, J24

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1. Introduction

Job performance is important because a high-performance workforce is essential for a firm's productivity. A high-performance workforce would contribute to the firm's cost-minimization, which is an essential behavior that most economic analyses assume (Brown, 1982). Employers need to understand which factors determine employees' job performance. This knowledge will help employers in choosing applicants with the potential for high performance.

Literature shows that psychological factors, such as the Big Five personality traits (including extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism) and self-esteem, are significant predictors of job performance (see Baumeister, Campbell, Krueger, & Vohs, 2003; Hogan & Holland, 2003; Hurtz & Donovan, 2000; Salgado, 1997). This study focuses on another core psychological concept, locus of control (LOC), and how it relates to job performance. LOC is defined as "a generalized attitude, belief, or expectancy regarding the nature of the causal relationship between one's own behavior and its consequences" (Rotter, 1966). People who believe that their own efforts produce outcomes in their lives have high LOC (internal LOC). In contrast, those who believe that external factors such as luck determine outcomes in their lives have low LOC (external LOC).

The possible mechanisms by which LOC affects job performance can be justified by the learned helplessness theory and the control theory. According to the theory of learned helplessness[1], people who frequently experience failure are gradually convinced that they cannot control situations, subsequently leading them to reduce their effort and stop participating in task-oriented behaviors (Brockner et al., 1983). Accordingly, external LOC type individuals will likely display motivational deficits and helplessness symptoms when encountering difficult situations (Peterson & Seligman, 1984). Hence, they will have low performance. The control theory[2], as noted by Lord and Hanges (1987), suggests three potential approaches that an individual will take when his performance is lower than his expectations. They are (1) putting more effort to achieve his goals,

[1]Learned helplessness, proposed by Maier and Seligman (1976), refers to individuals discontinuing their attempt to improve their current uncomfortable situations after enduring repeated aversive conditions beyond their control because they think they are helpless.

[2] Originated by Weiner (1948), control theory (or self-control theory) was presented in the context of human behavior and psychology by Carver and Scheier (1982). Self-control is a cognitive process that regulates behavior to achieve personal goals and allows individuals to constrain themselves from impulsive responses in behavior.

(2) lowering his standard, or (3) withdrawing from the task entirely. Accordingly, when discrepancies occur, internal LOC-type individuals are likely to take the first approach. Therefore, they should be better performers than those with an external LOC type who will likely take the second or third approach.

Studies in organizational behavior and psychology have examined the relation of LOC to job performance. Most of these studies consistently show that LOC significantly predicts job performance. Using a pool of 209 professional accountants, Chen and Silverthorne (2008) find that LOC significantly impacts job performance, job stress, and job satisfaction. Using a sample of 404 employees and 51 administrative staff members, Martin, Thomas, Charles, Epitropaki, and McNamara (2005) find that internal LOC type employees develop good quality leader-member relationships with their managers, which leads to positive workplace reactions, including job performance and job satisfaction. Ottley, Crouser, Ziemkiewicz, and Chang (2012), in an experiment involving 300 users of visualization design, find that variations in users' LOC lead to variations in their job performance. By conducting a meta-analysis, Judge and Bono (2001) show that LOC is one of the four self-evaluation traits (including self-efficiency, self-esteem, LOC, and emotional stability) that significantly predict job performance and job satisfaction. While meaningfully contributing to our understanding of the relation of LOC to job performance, these previous studies use cross-sectional data with small samples of individuals working in a specific field (e.g., accounting, financial services, and college students). Also, these studies analyze the relation of LOC to job performance at a single time point with an assumption that LOC is stable over time.

To address these limitations, our study draws longitudinal data from the Household Income and Labor Dynamics in Australia (HILDA) survey and develops a micro-econometric model to estimate the causal effect of LOC on job performance. We utilize the fixed effects panel data analysis technique, allowing LOC to change over time. While estimating micro-econometric equations allows us to obtain more accurate inferences of model parameters, longitudinal data enables controlling for the confounding effects of the unobserved individual-specific heterogeneity. Additionally, using longitudinal data, in which the LOC measurements are available over the years, allows us to capture the changes in LOC over time. Mainly, we analyze the changes in LOC over time using the method suggested by Cobb-Clark and Schurer (2012). The results reveal longitudinal variations in LOC (Appendix 2).

Another interesting feature of our paper is distinguishing job performance into two dimensions using exploratory factor analysis. Those two dimensions are task performance and adaptive performance.

Our findings reveal that LOC exerts a positive impact on the adaptive performance dimension; this implies that internal LOC type individuals are likely to be more adaptive to circumstances or changes perceived in the workplace, leading to better job performance. The result holds when we address the endogeneity of LOC by applying Lewbel's identification method (Lewbel, 2012) and control for attrition bias driven by panel survey.

The paper is structured as follows. Section 2 describes the model, data, and measurements. Section 3 presents the results and robustness checks. Section 4 concludes.

2. Methodology

2.1. Model and Empirical Strategy

To investigate the linear causal effect of LOC on job performance, we consider the longitudinal model below:

$$JP_{it} = \alpha_0 + \alpha_1 LOC_{i,t-1} + X_{i,t-1}\alpha_2 + u_i + \varepsilon_{it} \qquad (1)$$

where JP_{it} is a vector of two dimensions of individual's job performance[3] at time t, $LOC_{i,t-1}$ is individual's level of LOC at time $t-1$, $X_{i,t-1}$ is the vector of control variables lagged to $t-1$, u_i is the unobserved individual fixed effects; ε_{it} is the idiosyncratic errors.

We use the lag of LOC relative to job performance because LOC may be driven by contemporaneous job performance (Cobb-Clark & Schurer, 2012). In this case, the endogeneity issue resulted from reverse causality leads to an estimation bias of unclear sign and magnitude. Occasionally, lagged measures of LOC are utilized by researchers to eliminate any bias resulting from reverse causality or simultaneity (Cobb-Clark & Schurer, 2012).

It is well known that with the presence of the unobserved individual heterogeneity, u_i, ordinary least squares (OLS) results in biased estimates. The estimation strategies favored to deal with individual heterogeneity are random effects (RE) and fixed effects (FE) estimators. The FE model, which allows the correlation between explanatory variables and individual effects, seems more favorable for our analysis because there may be unobserved individual characteristics such

[3] We derive the two subdimensions of job performance, namely task performance and adaptive performance, in section 2.3.1

as family background and discount rates that may simultaneously correlate with an individual's LOC and job performance. The Hausman test[4] for regressions of both job performance's dimensions achieved p -values equal to zero up to four decimal points, suggesting that the FE model is preferred for our analysis to the RE model.

2.2. Data

We draw data from the longitudinal Household Income and Labor Dynamics in Australia (HILDA) survey. HILDA, which the Australian Government funds, collects nationally representative longitudinal information through face-to-face interviews and self-completion questionnaires. This annual survey started in 2001 and recently released wave 19 data (corresponding to 2019). More information on the sampling method and other technical aspects of the HILDA survey can be found in Watson and Wooden (2012).

This dataset is ideal for our analysis as it captures information on people's socioeconomic factors, job performance, and personality psychology, including LOC. While the measures of job performance are surveyed annually, the measures of LOC are surveyed once every four years. Since our empirical analysis uses the lag of LOC and control variables relative to job performance, we draw waves 8, 12, and 16 (corresponding to years 2008, 2012, and 2016, respectively) for job performance, and waves 7, 11, and 15 (corresponding to years 2007, 2011, and 2015, respectively) for LOC and other control variables. This constitutes three time points (hereon referred to as waves) in our model, i.e., t = {*2008, 2012, 2016*} paired with t-*1* = {*2007, 2011, 2015*}.

We focus on respondents in the working-age range (20 to 59 years old). After excluding individuals with missing answers and constraining the LOC data to the 99th percentile[5], the final sample corresponds to an *unbalanced panel* of 6,443 individuals (3,227 males and 3,216 females), equivalent to 9,928 observations (5,075 males and 4,853 females). Particularly, there are 2,770 observations in the first wave, 3,089 observations in the second wave, and 4,065 observations in the third wave.

2.3. Variable Measurement

2.3.1. Job Performance

[4] For Task performance regression, $\chi^2 = 202.07$. For Adaptive performance regression, $\chi^2 = 143.95$

[5] We exclude 0.05 percent of the lowest and 0.05 percent of the highest values of LOC from our analysis to mitigate the measurement error arising from self-reported LOC.

Job performance includes both behavior and output aspects (Sonnentag & Frese, 2002). Three dimensions of job performance are identified across the literature. First, task performance corresponds to job knowledge, organizational skills, and efficiency (Carlos & Rodrigues, 2016). Second, contextual performance corresponds to behaviors that enhance the organization's environment, such as persistent and extra effort, interpersonal skills, and compliance with the organizational rules (Borman & Motowidlo, 1997; Campbell, 1999; Johnson, 2001). Third, adaptive performance corresponds to the ability to deal with, respond to, and support organizational changes (Griffin, Neal, & Parker, 2007; Pulakos et al., 2002).

An individual's job performance can be evaluated through (1) objective organizational records of employee's output and (2) subjective evaluations, including rating by another (i.e., supervisor) and self-rating (Carlos & Rodrigues, 2016). To minimize the bias in evaluating job performance, it is ideal to use both objective organizational records and subjective evaluation. However, due to the nature of the HILDA survey, in this paper, job performance is evaluated through the self-rating method only, which can lead to biased estimates of LOC on job performance since employees tend to report higher than actual job performance, which is a limitation of this paper. To partially mitigate the bias issue due to the measurement error of job performance, we employ factor analysis to form interpretable aggregates of job performance dimensions. This method summarizes the coverability among observed measures using low-dimensional latent variables and accounts for the measurement error (Heckman, Pinto, & Savelyev, 2013).

Ten items are shortlisted to measure job performance. Answers range on a 7-point scale from 1 "Strongly disagree" to 7 "Strongly agree". A higher score represents better job performance. (Note: * require a reversed score to measure high job performance). These questions are:

JoPm_1: "I use many of my skills and abilities in my current job"

JoPm_2: "I don't have enough time to do everything in my job" *

JoPm_3: "I have to work fast in my job"

JoPm_4: "I have to work very intensely in my job"

JoPm_5: "My job requires me to take initiative"

JoPm_6: "My job provides me with a variety of interesting things to do"

JoPm_7: "My job often requires me to learn new skills"

JoPm_8: "My job is more stressful than I had ever imagined" *

JoPm_9: "I fear that the amount of stress in my job will make me physically ill" *

JoPm_10: "I worry about the future of my job" *

One issue with equation (1) is that job performance is potentially related to age (Ng & Feldman, 2008; Sarmiento, Beale, & Knowles, 2007; Sturman, 2003). Therefore, we standardize all items selected to measure job performance by the respondents' age (see Attanasio, Cattan, Fitzsimons, Meghir, & Rubio-Codina, 2020 for the age-standardization process).

We employ exploratory factor analysis (EFA) developed by Gorsuch (1983) to check dimensionality and establish dedicated measures. EFA leads to only 7 of 10 items to be retained for the analysis. These 7 items contribute to two factors corresponding to two dimensions of job performance, where dimension 1 - Task Performance is captured by items JoPm_1, JoPm_5, JoPm_6, and JoPm_7, and dimension 2 - Adaptive Performance is captured by items JoPm_2, JoPm_8, and JoPm_9. After identifying two dimensions of job performance, we apply Bartlett's (1937) approach to calculate the factor scores for each dimension. The EFA process to obtain the job performance's dimensions are displayed in Appendix 1.

2.3.2. Locus of control

HILDA surveys asked 7 questions regarding LOC in waves 7, 11, and 15. Answers range on a 7-point scale from 1 "Strongly disagree" to 7 "Strongly agree". These 7 questions are: (1) "I have little control over the things that happen to me"; (2) "There is really no way I can solve some of the problems I have"; (3) "There is little I can do to change many of the important things in my life"; (4) "I often feel helpless in dealing with the problems of life"; (5) "Sometimes I feel that I'm being pushed around in life"; (6) "What happens to me in the future mostly depends on me"; (7) "I can do just about anything I really set my mind to do".

From the 7 questions above, questions (1) to (5) measure external LOC, while questions (6) and (7) measure internal LOC. We reverse the score of question (1) to (5) so that the higher score implies more internal LOC.

We perform an internal consistency test by calculating Cronbach's alpha from these 7 questions. The Cronbach's alpha of 0.85 indicates that the set of 7 questions obtains high internal consistency. Following many previous studies (e.g., Cobb-Clark, Kassenboehmer, & Schurer, 2014; Cobb-Clark & Schurer, 2012; Kesavayuth, Ko, & Zikos, 2018; Lee & McKinnish, 2019), we calculate a single LOC index by taking the sum of the scores of 7 questions. Thus, the aggregate score of LOC ranges from 7 to 49, where higher scores indicate more internal LOC.

Due to the availability of measures of LOC in multiple years, we employ the approach suggested by Cobb-Clark and Schurer (2012) to investigate the changes in LOC over time. Appendix 2 reports the results of the analysis on the longitudinal variation of LOC.

Following Borghans et al. (2011), there exist measurement problems in personality psychology, where scores of LOC may be contaminated by people's efforts to make themselves look good. To partially mitigate the bias issue due to the measurement error of LOC, we constructed a cleaner LOC measure by trimming the LOC data at the 99th percentile[6].

Generally, while the change in LOC does not respond to demographic variables, health events, and the labor market, LOC may vary over the life cycle due to the aging process (Cobb-Clark & Schurer, 2012; Coleman & DeLeire, 2003). Therefore, we also standardize the raw scores of LOC by respondent's age (see Attanasio et al., 2020 for the age-standardization process).

2.3.3. Control variables

Socioeconomic factors are found to be important in determining job performance. Consistent with the literature, our job performance regression model controls for age, education, number of dependent children, work experience, organizational tenure, and dummy variables for gender, marital status, occupation, and working sector.

Moreover, we also control for physical health, mental health, wages, and job satisfaction. The impacts of physical health and mental health on job performance are well documented across the literature (e.g., Cropanzano & Wright, 1999; Sharifzadeh, 2013). Halkos and Bousinakis (2010) find that increased employees' job satisfaction increases their productivity. Hollenbeck, Noe, and Gerhart (1994) show that wages influence employees' job performance.

We also control for the Big Five personality traits since these traits are shown to determine job performance either particular to a job or across jobs (e.g., Hogan & Holland, 2003; Hurtz & Donovan, 2000; Salgado, 1997). Controlling for the Big Five would help us isolate the effect of LOC on job performance. The measures of control variables are reported in Table 1.

Table 1: Measurement of control variables

Control Variable	Measurement
Male	Dummy variable representing respondent's gender, = 1 if male and 0 if female

[6] Qualitatively similar results are obtained if we trim the sample at the 95th percentile. These results are available upon request.

Age	Respondent's age at June 30 of the survey year
Education	Number of years of education
Experience	Time in paid work (years)
Tenure	Time in current occupation (years)
Marital Status	Dummy variable representing the respondent's current marital status, = 1 if "legally married" and 0 = otherwise
Children	Number of dependent children
Job Satisfaction	Variable representing the overall job satisfaction of the respondent in the main job, measured by the question "All things considered, how satisfied are you with your job?". Answer ranges on a 0-10 scale with 0 = "totally dissatisfied", 10 = "totally satisfied")
Wages	Logarithm of current weekly gross wages and salary of the respondent's main job
Occupation	Dummy variable representing the respondent's current occupation, = 1 if managers or professionals and 0 = otherwise
Working Sector	Dummy variable representing the respondent's current working sector, = 1 if he/she is working in public sector, 0 if he/she is working in private sector
Health	
Physical Health	Measured by 21 questions from the 36-item Short Form Survey (SF-36) along 4 physical health dimensions (physical functioning, role-physical, body pain, and general health). Each dimension is provided in a standardized form on a 0-100 scale with higher score representing better physical health. We generate an aggregate score for physical health by computing the average of these 4 dimensions for each observation.
Mental Health	Measured by 14 questions from the 36-item Short Form Survey (SF-36) along 4 mental health dimensions (social functioning, role-emotional, mental health, and vitality). Each dimension is provided in a standardized form on a 0-100 scale with higher score representing better mental health. We generate an aggregate score for mental health by computing the average of these 4 dimensions for each observation.
Big Five personality traits	
Extraversion	Measured by the question "How well do the following words describe you? 1) talkative, 2) bashful, 3) quiet, 4) shy, 5) lively, 6) extroverted". The answer for each item ranges on a 7-point scale with 1 = "does not describe me at all", 7 = "describe me very well". The score for items 2, 3, and 4 are reversed. An aggregate score for Extraversion is generated by computing the average of these 6 items for each observation.
Agreeableness	Measured by the question "How well do the following words describe you? 1) sympathetic, 2) kind, 3) cooperative, 4) warm". The answer for each item ranges on a 7-point scale with 1 = "does not describe me at all", 7 = "describe me very well". An aggregate score for Agreeableness is generated by computing the average of these 4 items for each observation.

Conscientiousness	Measured by the question "How well do the following words describe you? 1) orderly, 2) systematic, 3) inefficient, 4) sloppy, 5) disorganized, 6) efficient". The answer for each item ranges on a 7-point scale with 1 = "does not describe me at all", 7 = "describe me very well". The score for items 3, 4, and 5 are reversed. An aggregate score for Conscientiousness is generated by computing the average of these 6 items for each observation.
Emotional Stability	Measured by the question "How well do the following words describe you? 1) envious, 2) moody, 3) touchy, 4) jealous, 5) temperamental, 6) fretful". The answer for each item ranges on a 7-point scale with 1 = "does not describe me at all", 7 = "describe me very well". The score for all items is reversed. An aggregate score for Emotional Stability is generated by computing the average of these 6 items for each observation.
Openness	Measured by the question "How well do the following words describe you? 1) deep, 2) philosophical, 3) creative, 4) intellectual, 5) complex, 6) imaginative". The answer for each item ranges on a 7-point scale with 1 = "does not describe me at all", 7 = "describe me very well". An aggregate score for Openness is generated by computing the average of these 6 items for each observation.

It is noteworthy that a variance inflation factor (VIF) analysis allows us to rule out potential multicollinearity regarding the choice of explanatory variables. We standardized our continuous health measures (physical and mental health), job satisfaction score, and the scores of the Big Five (so that the mean is 0 and the standard deviation is 1). The descriptive statistics for all our variables are reported in Table 2.

Table 2: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Job Performance				
Task Performance	0.00	1.15	-4.34	2.05
Adaptive Performance	0.00	1.17	-3.54	1.92
Locus of Control				
Raw score	39.33	6.85	20	49
Age-standardized score	0.00	1.00	-3.02	1.48
Age	41.28	10.69	20	59
Male	0.51	0.50	0	1
Education	13.15	2.36	0	18.5
Experience	21.19	10.74	0.08	46.03

Tenure	9.14	8.88	0.02	44
Marital Status	0.58	0.49	0	1
Children	0.91	1.10	0	7
Job Satisfaction	7.74	1.47	0	10
Wages	6.90	0.67	1.10	9.57
Occupation	0.41	0.49	0	1
Working Sector	0.29	0.45	0	1
Health				
Physical Health	82.64	15.11	3.75	100
Mental Health	79.03	15.52	5.5	100
Big Five				
Extraversion	4.44	1.08	1	7
Agreeableness	5.40	0.87	1	7
Conscientiousness	5.17	0.98	1	7
Emotional Stability	5.15	1.02	1	7
Openness	4.24	1.02	1	7

Note: The number of observations for each variable is 9,928.

3. Results

3.1. Main results

The estimated effects of LOC on two dimensions of job performance are presented in Table 3. Although the results of the Hausman test suggest that FE is more favorable for our analysis, besides estimates based on FE models with standard errors clustered at the individual level, estimates based on OLS and RE regressions are also reported for comparative purposes.

For dimension 1 of job performance - Task Performance, the OLS and RE estimates (Column 1 and Column 2) suggest that LOC positively predicts task performance (at p-values < .01). However, the FE estimates (Column 3) show that the effect of LOC on task performance, although still positive, is not significant.

For dimension 2 of job performance - Adaptive Performance, the estimates based on OLS, RE, and FE models suggest that LOC is positively related to adaptability. The corresponding coefficient estimates are highly significant at p-value <.01. This indicates that those with more internal LOC are likely to better adapt to their perceived conditions in the workplace, leading to better job performance. An increase of one standard deviation in LOC level corresponds with an increase of approximately 0.079[7] standard deviations in working people's adaptability.

These findings are in line with the previous organizational behavior studies (Chen & Silverthorne, 2008; Kalbers & Fogarty, 2005; Martin et al., 2005), which found that internal LOC type employees can better deal with job-related stress and have a better task-related performance than their counterparts of an external LOC type. One possible explanation is that internal LOC type employees are more effective in receiving and using information; they can also utilize their experience in their tasks leading to better results; at the same time, their beliefs in their efforts are more decisive than their counterparts with an external LOC (Rose & Vega, 1984).

Table 3: Locus of control and job performance (OLS, random effects, and fixed effects estimates)

	Job Performance					
	Dimension 1-Task Performance			Dimension 2- Adaptive Performance		
	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Locus of control	0.0918***	0.0825***	0.0139	0.176***	0.156***	0.0789***
	(0.0131)	(0.0131)	(0.0220)	(0.0139)	(0.0142)	(0.0246)
Male	-0.0297	-0.0327	.	0.140***	0.138***	.
	(0.0248)	(0.0279)	.	(0.0258)	(0.0287)	.
Age	-0.0182***	-0.0193***	-0.00143	0.00879***	0.00800***	0.107*
	(0.00261)	(0.00295)	(0.0676)	(0.00273)	(0.00299)	(0.0626)
Education	0.0293***	0.0364***	0.0510*	-0.0152**	-0.0189***	-0.00419
	(0.00545)	(0.00611)	(0.0284)	(0.00590)	(0.00650)	(0.0315)
Experience	0.0138***	0.0152***	-0.00562	-0.00661**	-0.00585*	-0.110*
	(0.00269)	(0.00305)	(0.0692)	(0.00285)	(0.00312)	(0.0646)
Tenure	0.00352***	0.00237*	-0.00431*	-0.00285**	-0.00287*	-0.00159
	(0.00128)	(0.00134)	(0.00240)	(0.00142)	(0.00148)	(0.00276)
Legally married	0.0481**	0.0457*	-0.0345	-0.0274	-0.00749	0.0333

[7] To investigate if the impact of LOC on adaptive performance varies by time, we include the interactions between dummy variables of time and LOC in the regression of adaptive performance. However, the two estimated coefficients of two interaction terms are not statistically significant. Therefore, we cannot conclude that the impact of LOC on adaptive performance varies by time.

	(0.0241)	(0.0260)	(0.0540)	(0.0254)	(0.0271)	(0.0640)
Number of dependent	0.0267***	0.0280***	0.0310	-0.00705	-0.0122	-0.0369
children	(0.0100)	(0.0105)	(0.0200)	(0.0107)	(0.0113)	(0.0247)
Physical health	-0.00391	0.000393	-0.00328	0.0437***	0.0385***	-0.000185
	(0.0130)	(0.0128)	(0.0210)	(0.0142)	(0.0144)	(0.0248)
Mental health	-0.0256*	-0.0163	0.00271	0.133***	0.118***	0.0394
	(0.0148)	(0.0148)	(0.0232)	(0.0162)	(0.0162)	(0.0270)
Job satisfaction	0.225***	0.189***	0.0909***	0.164***	0.140***	0.0523**
	(0.0129)	(0.0130)	(0.0195)	(0.0128)	(0.0134)	(0.0228)
Wages	0.214***	0.204***	0.163***	-0.263***	-0.258***	-0.209***
	(0.0208)	(0.0223)	(0.0486)	(0.0187)	(0.0199)	(0.0480)
Managers/ Professionals	0.438***	0.381***	0.140***	-0.250***	-0.219***	-0.103*
	(0.0247)	(0.0264)	(0.0495)	(0.0271)	(0.0284)	(0.0551)
Working in public sector	0.169***	0.163***	0.0863	-0.0436*	-0.0400	0.0656
	(0.0226)	(0.0251)	(0.0644)	(0.0246)	(0.0277)	(0.0780)
Extroversion	0.0766***	0.0749***	0.0185	0.00163	0.00315	-0.0226
	(0.0112)	(0.0122)	(0.0284)	(0.0117)	(0.0126)	(0.0324)
Agreeableness	0.0897***	0.0814***	0.0364	-0.0147	-0.00521	0.00602
	(0.0122)	(0.0128)	(0.0255)	(0.0128)	(0.0134)	(0.0271)
Conscientiousness	0.0359***	0.0309**	-0.00830	0.0266**	0.0270**	0.00206
	(0.0115)	(0.0124)	(0.0277)	(0.0123)	(0.0130)	(0.0292)
Emotional stability	0.0377***	0.0338***	0.00672	0.0872***	0.0817***	0.0177
	(0.0123)	(0.0128)	(0.0234)	(0.0132)	(0.0138)	(0.0276)
Openness	0.116***	0.0959***	0.0173	-0.0657***	-0.0631***	-0.0147
	(0.0122)	(0.0131)	(0.0268)	(0.0126)	(0.0134)	(0.0311)
Constant	-1.704***	-1.673***	-1.667	1.886***	1.892***	-0.515
	(0.151)	(0.161)	(1.377)	(0.144)	(0.153)	(1.290)
N	9,928	9,928	9,928	9,928	9,928	9,928

Notes: *p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses.

3.2. Heterogeneity

We conduct some estimates based on gender and job complexity to confirm if the positive effect of LOC on adaptive performance could be generalized to working individuals.

3.2.1. By Gender

The first idea is that gender is important in understanding behavior. Previous studies suggest that men's and women's LOC levels are significantly different (e.g., Maadal, 2020;

Sherman, Higgs, & Williams, 1997). Additionally, the performance of men and women on the job are also different due to: (1) physical and psychological differences (Goleman, 1995); (2) difference in risk-attitude (Blekesaune & Solem, 2005; Brown & Corcoran, 1997; M. Powell & Ansic, 1997); (3) interruption in women's career development due to family caring (Hochschild, 1997; Ornstein & Isabella, 1990); or (4) unequal treatment in workplace (Lyness & Thompson, 1997; G. N. Powell, Butterfield, & Parent, 2002). Therefore, we examine whether gender matters in the relation of LOC to job performance.

To achieve this, we separate the data by the gender of the respondents. The estimates in Column 1 and Column 2 of Table 4 suggest that the effect of LOC on job performance is significant only for males. To check if this difference is statistically significant, we use a *two-sample z-test*[8]. With a z-score = 76.77, we conclude that, in our data, males and females differ systematically in how LOC influences job performance.

3.2.2. By Job Complexity

Heywood et al. (2017) argue that an individual with internal LOC prefers more challenging and complex jobs, which are likely to require a high level of performance. To examine whether job complexity matters in the relation between LOC and job adaptability, we utilized a 7-point scale item of "My job is complex and difficult" (with possible answers ranging from 1 "Strongly disagree" to 7 "Strongly agree") to separate the data into two groups of highly complex jobs (> 4 points) and less complex jobs (=< 4 points). We conduct the two-sample z-test to test for statistically significant differences in the estimates. The z-score = 40.19 implies that job complexity matters in how LOC influences job performance (Column 3 and Column 4 of Table 4).

Table 4: Locus of control and adaptive performance by gender and job complexity: Fixed effects estimates

	Adaptive Performance			
	Female	Male	Highly complex jobs	Less complex jobs
	(1)	(2)	(3)	(4)
Locus of control	0.0457	0.105***	0.0775*	0.0436
	(0.0392)	(0.0308)	(0.0404)	(0.0366)

[8] $z = \frac{\hat{\beta}_{male} - \hat{\beta}_{female}}{\sqrt{\frac{SE^2_{male}}{N_{male}} + \frac{SE^2_{female}}{N_{female}}}}$, where $\hat{\beta}, SE,$ and N are the estimated coefficient, standard error, and number of observations of each sub sample.

All control variables	Yes	Yes	Yes	Yes
N	4853	5705	5114	4814

Notes: *p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses.

Taken together, our findings suggest that LOC drives adaptive job performance, especially among males with high complexity jobs.

3.3. Robustness

A potential concern is that the selection bias due to the panel survey can drive our results LOC may influence long term participation of the survey (Kesavayuth et al., 2018). Even though the reason is unclear, we would like to shed some light on this issue by comparing the mean of LOC of the two groups - the group of respondents staying in the survey in the following waves and the group of respondents leaving the survey in the following waves. The results in Table 5 show that on average, respondents staying in the survey in the following waves have higher LOC relative to those leaving the survey in the following waves.

Table 5: LOC of respondents staying in the survey in the following waves vs respondents leaving the survey in the following waves

	Obs	Mean	Std. Dev.
Respondents leaving the survey in the following waves [a]	4,089	-0.026	1.013
Respondents staying in the survey in the following waves	5,839	0.020	0.991
Total number of observations	9,928		

Notes: [a] includes respondents who are absent in the third wave or both second and third wave

To address this concern, we include a dummy variable that equals one if the respondent drops out of the survey in the following waves and zero otherwise. As is evident from Table 6, LOC continues to positively influence adaptive performance at p value <.05.

Table 6: Locus of control and adaptive performance with the dummy variable (1 if the respondent leaves the survey in the following waves, and 0 otherwise): Fixed effects estimates

	Adaptive performance
Locus of control	0.0789**
	(0.0330)
Leaving the survey in the following waves	-0.136*
	(0.0736)

All control variables	Yes
N	9928

Notes: *p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses.

Although we address the endogeneity issue of LOC resulting from age, LOC is still likely to be endogenous due to other sources. LOC might be subjected to measurement error. Also, there might be unobservable characteristics that simultaneously affect individuals' LOC and job performance. The potential endogeneity of LOC implies that the FE estimator could still be biased.

We employ Lewbel's identification method (Lewbel, 2012) to address the endogeneity issue. In Lewbel's method, internal instruments are constructed from a vector of variables, Z, that are uncorrelated with the covariance of heteroscedastic errors, where Z is a subset or equal to the vector of exogenous regressors. This approach is helpful when other identification sources, such as IVs, may not be available. Lewbel's method has been widely employed in recent studies of labor economics to deal with endogeneity (e.g., Emran & Shilpi, 2012; Kelly, Dave, Sindelar, & Gallo, 2014; Kesavayuth & Zikos, 2018; Mishra & Smyth, 2013, 2014).

We check our results' robustness using both Lewbel_IV estimators: two-stage least squares and two-step GMM (Baum & Schaffer, 2012; Lewbel, 2012). The diagnostics reported in Table 7 show that instruments generated using Lewbel's method satisfy both the overidentification test and the weak instrument test. The estimates presented in Column 1 and Column 2 of Table 7 show that LOC predicts adaptive performance positively (at p-value < .01), thus further supporting our prior findings.

Table 7: Locus of control and adaptive performance: Lewbel_IV estimates

	Adaptive Performance	
	Two-stage least squares	Two-step GMM
	(1)	(2)
Locus of control	0.263***	0.270***
	(0.0692)	(0.0685)
All control variables	Yes	Yes
N	9928	9928
Over Identification Test:		
Hansen's J Statistics	23.378	23.378
P-value	0.1373	0.1373

Weak Identification Test:		
Kleibergen-Paap rk Wald F statistic	11.877	11.877

Notes: *p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses.

4. Conclusion

Although psychologists and organizational behavior researchers have investigated the effect of LOC on job performance, there is no longitudinal evidence on this relationship. Using the longitudinal data from Australia, this study shows that LOC positively affects adaptive performance, leading to enhanced job performance among the working population. The results still hold when we try to address the endogeneity issue of LOC using Lewbel's identification method (Lewbel, 2012), as well as when we control for systematic dropouts to address the attrition bias driven by the longitudinal nature of panel survey.

This paper's findings complement the economic and psychological literature by presenting two key implications – the first is about the mechanism by which LOC affects job performance, and the second is about organizational practices.

First, our findings reveal a mechanism through which LOC determines job performance. LOC affects individuals' adaptability in the job, and as a result, affects their job performance. Individuals with an internal LOC, who have more decisive beliefs in their effort's effectiveness, can better cope with job-related stress and are more adaptive to perceived conditions or happenings in the workplace than their counterparts with an external LOC, subsequently resulting in higher productivity and job quality.

Second, from a practical perspective, it can be stated that employers can observe several useful organizational practices in this field. Firstly, employers could apply tests for recruitment procedures in which employees' LOC can be evaluated. Secondly, employers could invest in improving employees' LOC by providing them with knowledge on the LOC and directing them to learn practical skills to nourish their internal LOC. Finally, working individuals should recognize the value of strengthening their belief that they can control the events and happenings in their lives. LOC could help individuals yield psychological and economic returns from improved job performance.

Moreover, our paper also contributes to the economic field in the fashion that understanding the relationship between job performance and personality traits to choose a high-performance workforce is an important topic among economists. As noted by Brown (1982), "Selecting the best workforce from a pool of applicants is an essential function for a firm which hopes to survive competitive pressures. Evidence on how successfully firms perform this function is important for verifying the cost-minimizing behavior that most economic analyses assume."

A limitation of our paper is that the job performance measures used in our study are constructed by the self-rating method only. Although the questions from the survey can capture the general concept of job performance, which refers to people's behavior at work and can be assessed positively or negatively for the operations and development of the organization (Motowidlo, Borman, & Schmit, 1997), they do not capture all dimensions of job performance suggested by previous studies.

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Appendix 1. Exploratory Factor Analysis (EFA) for job performance measures

We employ exploratory factor analysis (EFA) developed by Gorsuch (1983) for the 10 selected items to check dimensionality and establish dedicated measures. Based on the literature on EFA, three conditions for extracting a factor are applied. First, only factors with eigenvalues >1 are extracted and retained. Second, only items with the highest factor loading that exceeds 0.4 on the expected factor and exceeds the second-highest factor loading by more than 0.1 (to avoid cross-loaded measures) are retained. Third, following Heckman (2013), we need at least three measures for each factor to achieve identification.

The eigenvalue suggests that only two factors can be extracted with eigenvalue of 2.92 and 1.49 for factor 1 and factor 2, respectively. Orthogonal varimax rotation after principal factor provides the pattern matrix in **Table 1.1** (only rotated factor loadings higher than 0.3 are displayed). Based on the rotated factor loadings achieved and our preset conditions for retaining items, we drop the items JoPm_3 and JoPm_4 in the list because they are cross-loaded. Also, we drop item JoPm_10 because it has the loading below 0.4. The final result with two factors constructed by 7 items is shown in **Table 1.2.**

Table 1.1: Pattern matrix of rotated factor loadings

Variable	Factor1	Factor2	Uniqueness
JoPm_1	0.6873		0.5233
JoPm_2		0.5777	0.5870
JoPm_3	0.3596	-0.4389	0.6781
JoPm_4	0.4972	-0.5387	0.4626
JoPm_5	0.707		0.4982
JoPm_6	0.7052		0.5006
JoPm_7	0.6104		0.5682
JoPm_8		0.7591	0.4223
JoPm_9		0.7264	0.4667
JoPm_10			0.8979

Table 1.2: Extracted Factors

Factor	Items	Dimension	Cronbach's alpha
Factor 1	JoPm_1 JoPm_5 JoPm_6 JoPm_7	Task performance	0.8
Factor 2	JoPm_2 JoPm_8 JoPm_9	Adaptive performance	0.76

Then, we apply Bartlett's (1937) approach to calculate the factor scores for further use. Since the Bartlett factor scores are based on the restricted minimization of mean squared error, it generates unbiased estimators of the true factor score (Hershberger, 2005). This approach only uses the common factor to calculate the factor scores and minimizes the sum of squared components for unique factors across the set of measures.

Appendix 2. Changes in the locus of control over time

Following Cobb-Clark and Schurer (2012), we compute the medium-run (2007-2011) and long-run (2007-2015) changes in LOC for 885 respondents with LOC data in all three waves to evaluate the variations in LOC over time. **Table 2.1** reports the distribution of medium and long-run changes in LOC.

Table 2.1: Distributions of medium and long-run changes in locus of control

	Duration	Mean	Std. Dev.	Min	Max
Changes in locus of control	Medium run	0.467	5.930	-19	26
	Long run	0.872	6.519	-23	24

Since seven LOC items are on a 7-point scale, the change in LOC score could range from -42 to +42, where the extremes would imply that an individual is completely externally controlled in one year $(LOC_{it} = 7)$ and completely internally controlled in another year $(LOC_{ik} = 49, t \neq k)$, and vice versa. We do not observe any such dramatic changes in our data. Among the individuals in our sample, on average, the mean LOC change is 0.5 for the medium run and 0.9 for the long run. The standard deviation of about 6.5 points for the long run implies that, on average, individuals change their response to each of the seven LOC items by approximately one point. Furthermore, it is important to note that about 88% and 90% of respondents change their LOC index in the medium and long run, respectively. These results provide evidence of variations in individuals' LOC over time.

To confirm this property of LOC, we compute the ratio between the between-variance and the within-variance of LOC. The ratio of 2.5 implies that LOC is a time-variant variable, as suggested by Plümper and Troeger (2007).