Economics Letters 230 (2023) 111249

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Does internal locus of control get you out of homelessness?

Santiago Budría[a,*,1], Alejandro Betancourt-Odio[b], Eszter Wirth[b]

[a] *Universidad Antonio de Nebrija, CEEAplA & IZA, Spain*
[b] *Universidad Pontificia Comillas, Spain*

ARTICLE INFO

Article history:
Received 15 February 2023
Received in revised form 23 June 2023
Accepted 3 July 2023
Available online 16 July 2023

ABSTRACT

This paper examines the role of internal locus of control in shaping transitions into homelessness. The data is taken from a longitudinal Australian dataset comprising a sample of vulnerable individuals. The results, based on a Wooldridge Conditional Maximum Likelihood (WCML) estimator, show that individuals with a high internal locus of control are significantly less likely to enter a homeless episode.

1. Introduction

One of the most exciting developments in economics in recent years has been the recognition that non-cognitive skills are central to individual decision-making and success. Recent research has shown that individuals with an internal locus of control (LOC) – one of the core non-cognitive skills in personality analyses – are more resilient (Etilé et al., 2021), expect higher returns from effort (Caliendo et al., 2022) and are more likely to engage in preventative behaviours (Bonsang and Costa-Font, 2022).

While these advances have improved our understanding of how personality is linked to individual outcomes, we currently know little about the association between LOC and primary achievements deemed necessary for a decent life, such as having adequate shelter. The paucity of data and low prevalence of traumatic events in general population surveys are partially responsible for this gap. Paradoxically, socially excluded groups are a population of special interest when studying interventions aimed at enhancing skills and alleviating social exclusion.

This paper takes a step in this direction by examining whether internal LOC can account for transitions into an extreme form of poverty: homelessness. We hypothesise that individuals with a high internal LOC are more prone to adaptive performance and aware of future needs, which prompts them to reduce housing risks. Homelessness has gained attention in the social agenda due to its consequences on social cohesion. In Australia, it is estimated that 50 out of every 10,000 people are currently homeless (Batterham, 2022).

We use data from Journeys Home (JH), a micro survey representative of the population experiencing disadvantages in all standard economic and social dimensions. The econometric approach is based on the Wooldridge Conditional Maximum Likelihood (WCML) estimator. The paper shows that individuals with a high internal locus of control are significantly less likely to enter a homeless episode. This result is robust to several sensitivity checks, including controlling for the potential endogeneity of LOC and non-random attrition. Further details on the WCML approach and alternative estimation methods are provided in Appendix.

2. Data and methods

The JH is drawn from a broad spectrum of a disadvantaged population (Melbourne Institute, 2014). It has a panel structure, with respondents being interviewed six times at six-monthly intervals. We restrict the sample to participants aged 20 to 59, noting that non-cognitive skills are relatively stable among adults (Borghans et al., 2008).

Our main explanatory variable of interest is LOC, which is assessed by seven questions from Pearlin and Schooler's (1978) questionnaire of coping efficacy. The responses are coded on a five-point Likert scale ranging from 1 (*strongly agree*) to 5 (*strongly disagree*), which yields a total score of 5 to 35 points. After conducting a factor analysis, we extract a single latent factor and identify separate loadings for each item. These weights are used to construct a continuous measure interpretable as internal LOC. Those believing that life's outcomes are determined by their own decisions (external factors such as luck) score high (low) on our LOC measure. The index is normalised to have zero mean and unit variance. Because this information is available only in wave

* Correspondence to: Department of Business Administration, Universidad Nebrija, C/de Sta. Cruz de Marcenado, 27, 28015 Madrid, Spain.
E-mail address: sbudria@nebrija.es (S. Budría).

1 The author gratefully acknowledges the financial support provided by the R&D Program in Social Sciences and Humanities by the Autonomous Community of Madrid, Spain, OPINBI project (Ref: H2019/HUM-5793), and the 2019 I+D+i National Projects and 2021 Strategic Projects Oriented to the Ecological and Digital Transition by the Spanish Ministry of Sciences and Innovation (Refs: PID2019-111765GB-I00 and TED2021-132824B-I00). We also thank seminars participants at the III Workshop on Equality of Opportunities, Social Inclusion and Welfare (Madrid, April 2023) for their comments, José María Labeaga for valuable insights and discussions and an anonymous referee for constructive remarks.

https://doi.org/10.1016/j.econlet.2023.111249
0165-1765/

6 of the JH, we assume LOC is time-invariant over the estimation period.

The JH contains detailed information on individuals' housing situation. We adopt a narrow definition of homelessness according to which individuals are homeless if they are (i) sleeping rough in cars or squatting in an abandoned building ('primary' homelessness, as defined by the Australia Bureau of Statistics, ABS, 2011) or (ii) living in emergency or crisis accommodation ('secondary' homelessness). This criterion applies to 9.4% of the JH sample and is closely aligned with much of the research evidence for the U.S. and Australia (Cobb-Clark et al., 2016).

2.1. Empirical strategy

We model homelessness transitions as:

$$H_{it} = \mathbf{1}\ \boldsymbol{if}\ \left(\rho H_{it-1} + X'_{it}\beta + \gamma LOC_i + c_i + u_{it} > 0\right) \tag{1}$$

$(i = 1, \ldots, N)$; $(t = 2, \ldots, T)$, where H_{it} is a dummy variable that takes the value of one if the individual is homeless and zero otherwise, X_{it} is a set of relevant confounders, c_i stands for unobservable heterogeneity, and u_{it} is white noise. We deal with the initial condition problem following Wooldridge (2005) and define an auxiliary distribution of the unobserved individual effect which is conditioned on the initial value H_{i1} and the within-means of the time-variant explanatory variables, $\overline{X}_i$,

$$c_i|H_{i1},\ X_{it} \sim N\left(\vartheta_0 + \vartheta_1 H_{i1} + \overline{X}'_t\vartheta_2, \sigma_\xi^2\right) \tag{2}$$

$$c_i = \vartheta_0 + \vartheta_1 H_{i1} + \overline{X}'_i\vartheta_2 + \xi_i$$

with $\xi_i \sim N\left(0, \sigma_\xi^2\right)$.[2] A consistent estimation of Eq. (1) crucially relies on the correct specification of c_i and the assumption that $E\left(H_{it-1}u_{it}\right) = 0$. In the Appendix we allow for less restrictive assumptions. Vector X_{it} includes the variables described in Table 1, which reports summary statistics and the marginal probability effects (MPEs) from the model.[3]

3. Results

Homelessness is a self-perpetuating state, with the reference individual being about 5.9 percentage points (pp) more likely to be homeless at time t if he/she was homeless at $t-1$. This uncovers a strong homelessness trap among vulnerable individuals in Australia and is consistent with the negative duration dependence reported in earlier work (Cobb-Clark and Kettlewell, 2021). The coefficient of homelessness at the initial period is significantly greater than zero, thus suggesting that initial homelessness is due to an earlier history of chronic poverty and unobserved characteristics that hamper a person's quality of life.

3.1. Is LOC related to homelessness transitions?

Individuals with a high LOC are less likely to suffer a homelessness spell. The estimate – a 1.3 pp decrease in the outcome probability for a one standard deviation increase in LOC – is non-negligible if we compare it with the sample average probability of being homeless (9.4%). The estimate is conditional on previous homelessness status; a condition that in our WCML setting captures the entire history of the right-hand-side variables, including those (employment, income, and schooling, among others) that may have been influenced by LOC at earlier stages of the individual's life.

The likelihood of homelessness is significantly lower among women and related to changes in marital status, with marriage representing a buffer against home loss. The coefficient of income

Table 1
Locus of control and homelessness dynamics.

	Sample average	Homeless Model 1 MPE
Internal Locus of Control (LOC)	23.0552	-0.0132^{***}
	(6.2058)	(0.0035)
Homeless_{t-1}	0.0939	0.0588^{***}
	(0.2918)	(0.0116)
Homeless_1	0.1289	0.0522^{***}
	(0.3351)	(0.0114)
Previous homeless experience	0.9541	−0.0023
	(0.2090)	(0.0203)
Employed	0.2323	0.0062
	(0.4223)	(0.0144)
Inactive	0.5287	0.0027
	(0.4992)	(0.0084)
Ln (Income)	6.0659	-0.0195^{*}
	(0.4979)	(0.0117)
Woman	0.4347	-0.0234^{***}
	(0.4957)	(0.0085)
Bad health	0.1265	0.0003
	(0.3325)	(0.0101)
Age	35.0410	−0.0027
	(11.159)	(0.0027)
Age^2	1339.888	0.0001
	(821.313)	(0.0001)
Tertiary education	0.3638	-0.0178^{*}
	(0.4811)	(0.0106)
Upper secondary (12 years of schooling)	0.1137	−0.0107
	(0.3173)	(0.0143)
Lower secondary (10–11 years of schooling)	0.4777	−0.0121
	(0.4779)	(0.0099)
Single	0.5519	0.0416^{***}
	(0.4973)	(0.0099)
Divorced	0.2243	0.0228^{*}
	(0.4171)	(0.0123)
Widowed	0.0127	0.0710^{**}
	(0.1134)	(0.0304)
Ln (Children)	0.5298	-0.0707^{**}
	(0.5900)	(0.0275)
Lives in major urban area	0.7734	0.0215^{**}
	(0.4186)	(0.0083)
Has a drug/alcohol addiction	0.1670	0.0082
	(0.3730)	(0.0083)
Has social support	3.9064	-0.0141^{***}
	(1.0446)	(0.0031)
Victim of physical violence	0.1597	0.0283^{***}
	(0.3663)	(0.0076)
Victim of sexual violence	0.0185	0.0581^{***}
	(0.1349)	(0.0204)
Regional per capita GDP	1.3903	0.0060^{***}
	(2.1214)	(0.0015)
Regional unemployment rate	5.5992	0.0069
	(0.7894)	(0.0049)
Region and wave fixed effects		Yes
No. of observations	4976	4976

Notes: (i) Source: JH, 6 waves; (ii) standard errors in parenthesis; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The set of controls includes a set of binary indicators that capture whether the respondent (i) has a problem of drug or alcohol addiction; (ii) can rely on networks of mutual support and community ties; (iii) has experienced either physical or sexual violence in the last 6 months; and (iv) has never experienced a homelessness episode before participating in the JH survey. This information captures life circumstances and non-observables that may impact an individual's financial strain and, ultimately, the individual's housing status. Regional per capita GDP, the unemployment rate, and region and wave fixed effects are included to account for the stance of the business cycle and regional disparities.

[2] Although the LOC measure may be subject to measurement error, we assume that the way individuals self-report such variables depends on individual traits or, in other words, that the individual fixed effect of the model absorbs the individual specific measurement error. Because the remaining measurement error is expected to produce attenuation bias, the estimates should be interpreted as a lower bound of the effect size.

[3] The MPEs have been calculated at the means of covariates.

Table 2
Locus of control and homelessness dynamics — selected groups.

	Homeless					
	Never unemployed	Constant schooling	Unchanged marital status	No death of relative/family member	Never physically/ sexually abused	No health/disability condition
Internal Locus of Control (LOC)	−0.0130***	−0.0128***	−0.0132***	−0.0117***	−0.0100**	−0.0110***
	(0.0039)	(0.0037)	(0.0039)	(0.0038)	(0.0041)	(0.0040)
Full set of controls	Yes	Yes	Yes	Yes	Yes	Yes
Region and wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	4504	3908	3900	3727	2951	2559
	Homeless					
	Men	Women	Secondary education or more	Less than secondary education	Young (≤40)	Old (>40)
Internal Locus of Control (LOC)	−0.0088*	−0.0172***	−0.0154***	−0.0117**	−0.0105***	−0.0126*
	(0.0041)	(0.0055)	(0.0041)	(0.0054)	(0.0037)	(0.0065)
Full set of controls	Yes	Yes	Yes	Yes	Yes	Yes
Region and wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	2257	2719	2375	2601	3245	1731

Notes: (i) Source: JH, 6 waves; (ii) standard errors in parenthesis; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

has the expected sign yet is significant only at the 10% level.[4] Homelessness risk is lower among those with a tertiary education and who have social support. Reversely, individuals living in an urban area and victims of physical or sexual harassment are more likely to be homeless. Variations in the regional employment rate fail to attract a significant coefficient, while individuals living in affluent areas are more likely to be homeless, perhaps due to the relatively high prevalence of homelessness in large, wealthy cities (Sydney, Melbourne, and Brisbane).[5]

4. Discussion

4.1. Endogeneity of LOC

The findings of this paper rely strongly on the assumption that LOC is a time-invariant attribute. There are reasons why this may be considered a reasonable assumption. Firstly, the most relevant factor accounting for changes in non-cognitive skills is aging, with short-run variations in personality being very concentrated among the young or old (Borghans et al., 2008). We limit this channel by restricting the sample to adults and relying on the short time span offered in the JH (six semesters between November 2011 and March 2014). Secondly, changes in LOC following life shocks, including illnesses, imprisonment, pregnancy, and unemployment, among others, tend to be economically negligible (Cobb-Clark and Schurer, 2013). These observations limit the risks of reverse causality in our setting.

Notwithstanding, we consider the possibility that the LOC measure extracted from wave 6 of the panel may not fully represent an individual's LOC during the entire period. In Table 2 we limit the potential impact of life events on LOC by focussing on individuals who have never been exposed to potentially relevant life shocks, including (i) unemployment episodes; (ii) changes in educational attainment; (iii) changes in marital status; (iv) the death of a relative or family member; (v) physical or sexual violence during the sample period; and (vi) a long term health/disability condition causing restrictions. In all cases, the estimates are well-defined and do not depart much from the previous findings, which suggests that the extent of attenuation bias in the baseline estimates, if any, is very limited.

Given that LOC may differ across socio-economic groups, in the bottom part of the table we split the sample into gender, schooling, and age categories. The association between LOC and homelessness remains negative and significant, particularly among women and individuals with a secondary education or more.

4.2. Potentially endogenous covariates, definition of homelessness, and additional controls

Table 3 presents results when variables potentially endogenous with LOC, such as income, labour status, schooling, and health condition are dropped from the specification (Model 2), and when these and the remaining covariates are omitted (Model 3). These sensitivity analyses result in a slight increase in the effect size. We also examine the extent to which the results hold when granular controls for health and financial condition (described in the Table) are included in the regressions (Model 4). In the next columns we show that, relative to the baseline model, the influence of LOC is notably reduced when accounting for the most severe form of homelessness, while it remains practically unchanged when we adopt a broad definition of homelessness.

4.3. Non-random attrition

Although retention rates are remarkably high in the JH (yearly average = 96.5%), the non-random exit and entry of individuals for reasons related to homelessness is a potential concern. To investigate this issue, we regressed a dummy equal to 1 for individuals who attrit at wave $t+1$ on homelessness and all the controls at wave t. Although dropouts are not significantly related with homelessness ($p = 0.492$), in Table 3 (last column) we report the results from a balanced panel in which the longitudinal weights provided by the JH have been used to limit potential biases arising from differential non-response.[6]

[4] The estimates shown in the table only capture the effect of variations in the explanatory variables. The effect of the time-averaged-value of all time-variant variables is embedded in the individual fixed effect.

[5] The prevalence of homelessness in these cities more than doubles the sample average. Housing affordability pressures are higher in capital cities than in regional areas. Moreover, among the eight Australian capital cities, Sydney, Melbourne, and Brisbane rank at least in the top four by number of affordability measures, including the proportion of household income required to afford a median mortgage and the dwelling price to income ratio (CoreLogic Australia, 2018).

[6] The longitudinal weights are calculated to correct for endogenous attrition. A full analysis of panel attrition and details of the construction of the balanced-panel weights can be found in the wave 6 technical report (Melbourne Institute, 2014). In our sample, gender ($p = 0.04$), singlehood (0.03), and divorce (0.02) correlate negatively with the probability of attrition.

Table 3
Locus of control and homelessness dynamics — sensitivity analyses.

	Homeless			Primary	Primary, secondary or	Homeless-
	Model 2	Model 3	Model 4	homeless	tertiary homeless	Balanced panel
Internal Locus of Control (LOC)	−0.0136***	−0.0214***	−0.0122***	−0.0024***	−0.0122**	−0.0126***
	(0.0034)	(0.0038)	(0.0033)	(0.0009)	(0.0061)	(0.0032)
Controls for income, labour status, schooling and health removed	Yes	No	No	No	No	No
All controls removed	No	Yes	No	No	No	No
Expanded set of controls (granular financial and health condition)[a]	No	No	Yes	No	No	No
Region and wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	4976	4976	4872	4976	4976	3644

Notes: (i) Source: JH, 6 waves; (ii) Standard errors in parenthesis; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a]This includes a set of 20 binary controls for: heart or circulatory condition, diabetes, asthma, chronic bronchitis or emphysema, cancer, problems with liver, arthritis, gout or rheumatism, epilepsy, kidney disease, hepatitis C, chronic neck or back problems, intellectual disability, acquired brain injury, bipolar affective disorder, (manic depression), schizophrenia, depression, post traumatic stress disorder, anxiety disorder, pending debts and gambling problems.

5. Conclusions

Evidence on the relationship between non-cognitive skills and the ability to fulfil primary needs among vulnerable populations (e.g., having a home) is practically non-existent. This paper takes a step towards filling this gap. The results show that individuals with a high internal locus of control are significantly less likely to enter a homeless episode. This result is robust to several sensitivity checks, even when including variables potentially endogenous with LOC, such as income, labour status, schooling, and health. From a theoretical standpoint, this may lend support to the notion that the way people respond to housing stressors, namely through their choice of coping and problem-solving mechanisms, depends on LOC. Considering our results, an integrated approach that goes beyond financial assistance and considers the role of individual traits may prove useful to identify key risk groups. Moreover, interventions from very early ages aimed at reinforcing specific skills among families and individuals at risk of social exclusion may result in more targeted social policies.

Data availability

The authors do not have permission to share data.

Appendix

The WCML estimator exhibits three main features, as it (i) takes account of the unobserved heterogeneity that surrounds homelessness transitions; (ii) controls for homelessness state dependence; and (iii) addresses the 'initial conditions' problem, i.e., the possibility that housing status at the start of the observation period is endogenously determined by the individual's past history. The auxiliary distributional assumption on the individual-specific effects allows the model to address two concerns, namely the potential correlation between (i) the unobserved heterogeneity and the regressors of the model, i.e., $E(X_{it}c_i) \neq 0$; and (ii) the unobserved heterogeneity and initial value of the dependent variable, i.e., $E(H_{i1}c_i) \neq 0$.

Nonetheless, the WCML approach relies on the assumption that the lagged dependent variable is independent from the composite error process, a condition that may be violated. To address this concern, in this Appendix we present two complementary exercises. Firstly, we resort to Arellano et al.'s (1999) method of sequentially censored subsamples according to which individuals without censored past observations ($H_{it-1} = 1$ in our case) are exogenously selected for the purpose of estimating the dynamics of the dependent variable. Although the selection process is an issue, in the censored subsample $E(H_{it-1}u_{it}) = 0$. The results in the first column of Table A.1 show that with this approach the LOC effect is −3.76 pp. Still, the estimate is significant only at the 10% level, probably due to the small sample size.

The second exercise, based on a two-stage Generalized Method of Moments (GMM) estimation procedure, provides similar point estimates. We start by taking first differences of a linear version of Eq. (1) to purge the individual-specific effect from the model:

$$\Delta H_{it} = \rho \Delta H_{it-1} + \Delta X'_{it}\beta + \Delta u_{it} \tag{A.1}$$

Although this approach comes at the cost of abstracting from the binary nature of the dependent variable, it provides a venue for more flexible assumptions because it does not require a distributional assumption on c_i. Noting that in the resulting model there is still correlation between the differenced lagged variable and the disturbance process (the former contains H_{it-1} and the latter contains u_{it}), we follow Arellano and Bond (1991) and instrument ΔH_{it-1} with all lags of H_{it-j}, for $j \geq 2$. This requires that $E(H_{it-j}\Delta u_{it}) = 0 \;\; \forall j \geq 2$ – a moment condition that can be tested – for the estimator to be unbiased and consistent.

However, this strategy is not directly applicable to our setting insofar as LOC is a time-invariant variable that disappears after taking first differences. Kripfganz and Schwarz (2019) propose a two-stage estimation procedure to identify the coefficients of invariant characteristics in the context of GMM models. The procedure consists of estimating Eq. (A.1) in a first stage and then regressing the first-stage residuals on the time-invariant regressors. Specifically,

$$\begin{aligned} &H_{it} - \hat{\rho}H_{it-1} - X'_{it}\hat{\beta} = \gamma LOC_i + \epsilon_{it}, \quad \text{with} \\ &\epsilon_{it} = c_i + u_{it} - \left(\hat{\rho} - \rho\right) H_{it-1} - X'_{it}\left(\hat{\beta} - \beta\right) \end{aligned} \tag{A.2}$$

where $\hat{\rho}$ and $\hat{\beta}$ are the first-stage estimates. In Table A.1 we present the estimation results of Kripfganz and Schwarz's two-stage model with GMM-type instruments, standard instruments for the strictly exogenous regressors, and Windmeijer-corrected robust standard errors (endogenous regressors: lagged dependent variable, income, and employment status; predetermined variables: education, marital status, number of children, health, and addictions; strictly exogenous: the remaining variables). We include results with and without collapsed instruments and under different moment conditions depending on whether they are linear or nonlinear as suggested by Chudik and Pesaran (2022). Although the first-stage estimates (not reported) vary between 10% to 20% across specifications, the LOC coefficients are practically identical across columns and almost double the baseline estimate from the linear version of Eq. (1) (last column).

In the bottom part of the table, the test for absence of serial correlation in the first-differenced errors of the first stage show that there is no second-order serial correlation. We also report

Table A.1
Locus of control and homelessness dynamics — sequentially censored subsamples and 2-step GMM.

	Sequentially censored subsamples	Two-step GMM estimator (Linear moments)		Two-step GMM estimator (Non-Linear moments)		Linear WCML estimator
		Full set of instruments	Collapsed instruments	Full set of instruments	Collapsed instruments	
Internal Locus of Control (LOC)	−0.0376* (0.0211)	−0.0324*** (0.0088)	−0.0294*** (0.0087)	−0.0311*** (0.0084)	−0.0281*** (0.0087)	−0.0161*** (0.0050)
No autocorrelation of order 1 (Prob > |z|)	–	0.0000	0.0000	0.0000	0.0000	–
No autocorrelation of order 2 (Prob > |z|)	–	0.7613	0.8823	0.9500	0.9425	–
Valid overidentifying restrictions (Prob > chi2)	–	0.2382	0.9134	–	–	–
No. of observations	476	3660	3660	3660	3660	4976

Notes: (i) Source: JH, 6 waves; (ii) standard errors in parenthesis; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hansen's J-test to check the validity of the overidentifying restrictions for the first stage of the model with linear moment conditions (the second stage is exactly identified, while the test is not defined under non-linear conditions). The null hypothesis (instrument validity) is not rejected.

References

ABS, 2011. Discussion Paper: Methodological Review of Counting the Homeless, 2006. Cat No 2050.0.55.001, Australian Bureau of Statistics, Canberra.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econom. Stud. 58, 277–297. http://dx.doi.org/10.2307/2297968.

Arellano, M., Bover, O., Labeaga, J.M., 1999. Autoregressive models with sample selectivity for panel data. In: G.S., Maddala, Hsiao, C., Lahiri, K., Lee, L., Pesaran, M.H. (Eds.), Analysis of Panels and Limited Dependent Variable Models. Cambridge University Press, Cambridge, UK, pp. 23–48.

Batterham, D., 2022. Magnet mobility myths: exploring geographical mobility amongst people experiencing, or at-risk of, homelessness in Australia. Int. J. Hous. Policy 1–23. http://dx.doi.org/10.1080/19491247.2022.2072662.

Bonsang, E., Costa-Font, J., 2022. Buying control? 'Locus of control' and the uptake of supplementary health insurance. J. Econ. Behav. Organ. 204, 476–489. http://dx.doi.org/10.1016/j.jebo.2022.10.035.

Borghans, L., Duckworth, A.L., Heckman, J.J., Ter Weel, B., 2008. The economics and psychology of personality traits. J. Hum. Resour. 43 (4), 972–1059. http://dx.doi.org/10.3368/jhr.43.4.972.

Caliendo, M., Cobb-Clark, D.A., Obst, C., Seitz, H., Uhlendorff, A., 2022. Locus of control and investment in training. J. Hum. Resour. 57 (4), 1311–1349. http://dx.doi.org/10.3368/jhr.57.4.0318-9377R2.

Chudik, A., Pesaran, M.H., 2022. An augmented Anderson–Hsiao estimator for dynamic short-T panels. Econometric Rev. 41 (4), 416–447. http://dx.doi.org/10.1080/07474938.2021.1971388.

Cobb-Clark, D.A., Herault, N., Scutella, R., Tseng, Y.P., 2016. A journey home: What drives how long people are homeless? J. Urban Econ. 91, 57–72. http://dx.doi.org/10.1016/j.jue.2015.11.005.

Cobb-Clark, D.A., Kettlewell, N., 2021. Psychological, social and cognitive resources and the mental wellbeing of the poor. PLoS One 16 (10), e0258417. http://dx.doi.org/10.1371/journal.pone.0258417.

Cobb-Clark, D.A., Schurer, S., 2013. Two economists' musings on the stability of locus of control. Econ. J. 123 (570), F358–F400. http://dx.doi.org/10.1111/ecoj.12069.

CoreLogic Australia, 2018. 25 Years of Housing Trends. CoreLogic, Available at: https://www.aussie.com.au/content/dam/aussie/documents/home-loans/aussie_25_years_report.pdf.

Etilé, F., Frijters, P., Johnston, D.W., Shields, M.A., 2021. Measuring resilience to major life events. J. Econ. Behav. Organ. 191, 598–619. http://dx.doi.org/10.1016/j.jebo.2021.09.0040167-2681.

Kripfganz, S., Schwarz, C., 2019. Estimation of linear dynamic panel data models with time-invariant regressors. J. Appl. Econometrics 34 (4), 526–546.

Melbourne Institute, 2014. Journeys Home: Wave 6 Technical Report (Report Prepared for the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs). Melbourne Institute of Applied Economic and Social Research, Melbourne.

Pearlin, L.I., Schooler, C., 1978. The structure of coping. J. Health Soc. Behav. 2–21.

Wooldridge, J.M., 2005. Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models. Rev. Econ. Stat. 87 (2), 385–390. http://dx.doi.org/10.1162/0034653053970320.