Earnings Dynamics and Measurement Error in Matched Survey and Administrative Data

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Disclaimer

The results in this working paper are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand. The opinions, findings, recommendations, and conclusions expressed in this working paper are those of the authors, not Statistics NZ, or Motu Economic and Public Policy Research Trust. Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this working paper have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz. The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Abstract

This paper analyses the measurement error and earnings dynamics of two sources of individuals' annual earnings from Statistics New Zealand's Survey of Family, Income and Employment (SoFIE) and administrative linked employer-employee data (LEED) earnings reported in the Integrated Database Infrastructure (IDI). First, SoFIE reported earnings are 2-4% lower than LEED earnings on average, and slightly more variable; while the difference between the two reported earnings accounts for 25-30% of the variance in either report. Second, we reject the joint hypothesis that SoFIE earnings are reported with classical measurement error and LEED earnings are recorded without error. We estimate that the statistical reliability of LEED measured earnings (0.87{0.91) is higher than that of SoFIE earnings (0.83{0.85). Third, the differences between SoFIE and LEED earnings are negatively correlated with both individuals' average (LEED) earnings over the sample period and their annual transitory deviations. These differences can be characterised longitudinally by both persistent and serially correlated transitory factors. Fourth, we formulate and estimate a model for SoFIE and LEED earnings, which includes dynamics for true earnings and for measurement errors in both SoFIE and LEED. Female earnings are more variable than males', due both to permanent and transitory effects, and transitory shocks are relatively stronger for women. Allowing for measurement error in LEED, we find no evidence of mean-reverting error in SoFIE. Fifth, the models imply measurement errors dominate the observed changes in male earnings, and account for large fractions of the changes in female earnings.

JEL codes

C33

Keywords

Panel data, earnings dynamics, measurement error, validation study

Summary haiku

When we understand
admin data has errors,
surveys don't look bad.

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1 Introduction

There is an extensive literature characterising and estimating the dynamic properties of individuals' earnings (for a summary see, Meghir and Pistaferri, 2011). These models typically include a permanent component of earnings, specified as a random walk, a low-order autoregressive moving-average (ARMA) transitory component and, recognising the presence of measurement error in reported earnings, a purely transitory component of earnings variation to explicitly account for measurement error (e.g. MaCurdy, 1982; Abowd and Card, 1989; Meghir and Pistaferri, 2011).

A large literature on measurement error in survey data has also developed (for a summary see, Bound et al., 2001), and particularly in reported earnings (e.g. Bound and Krueger, 1991; Pischke, 1995; Kapteyn and Ypma, 2007; Abowd and Stinson, 2013). Using data from validation studies, which collect a second measure of earnings, the assumption of random classical measurement errors in survey reported earnings is strongly rejected when the second "validated" measure is considered true (e.g. Bound and Krueger, 1991; Pischke, 1995). These studies find evidence of negative correlation between measurement error and the validated true earnings, and conclude that there is mean-reversion in reported earnings. More recent studies that compare survey and administratively-collected earnings recognise that the administrative earnings measure may also contain errors (Kapteyn and Ypma, 2007; Abowd and Stinson, 2013). In fact, Kapteyn and Ypma (2007) conclude that the established finding of mean-reverting measurement error in survey earnings is not robust to allowing for error in the administrative earnings.

In this paper we exploit rich longitudinal data on individuals earnings from two sources to characterise the measurement error in each, and use this characterisation to identify and estimate the dynamics of the underlying true earnings. The data comes from Statistics New Zealand Integrated Data Infrastructure (IDI), which provides an extremely rich repository of linked data from various sources. Our primary source of data is Statistics New Zealand's Survey of Family, Income and Employment (SoFIE), which was a household panel survey over 8 annual waves from 2002/3–2009/10, and provides a panel sample of individuals' annual earnings. Our second source of earnings data is administrative linked employer employee data (LEED) within the IDI, which covers individuals' monthly earnings from Inland Revenue's (IRD) Employer Monthly Schedule (EMS) for the population of earners who have tax withheld at source. The SoFIE sample of individuals is matched to the LEED data to provide an 8-year panel sample of annual earnings from these two sources.

The paper makes two contributions to the literature. First, the rich longitudinal data facilitates a detailed anaysis of the measurement errors in the alternative measures of individuals' earnings, and contributes to the methodological literature on measurement error in earnings. We find that SoFIE reported earnings are 2-4% lower than LEED earnings on average, and slightly more variable. Although the average difference between the two reported earnings is small, there is substantial variability, with differences accounting for 25-30% of the variance in either source of reported earnings. We reject the joint hypthesis that SoFIE reported earnings are measured with classical measurement error and LEED earnings are recorded without error. A cross sectional comparison of the the reported earnings implies the statistical reliability of earnings measured in LEED (0.87–0.91) is higher than in SoFIE (0.83–0.85). Consistent with the earnings validation literature we find that the differences between SoFIE and LEED earnings are negatively correlated with both individuals average (LEED) earnings over the sample period and their annual transitory deviations. Longitudinally, the differences are characterised by both persistent and transitory factors; the latter consistent with a low-order autoregressive moving average (ARMA) model.

Second, by accounting for the measurment error in reported earnings, the paper provides a contribution to the substantive literature on earnings dynamics. We formulate and estimate a model for SoFIE and LEED earnings, which includes dynamics for true earnings together with specifications for the measurement errors in SoFIE and LEED. Under the conventional assumption that LEED earnings are measured without error, the estimated model is consistent with the standard result of mean-reversion in SoFIE errors. However, when we allow for measurement error in LEED earnings, this result is overturned. We estimate that measurement errors account for 70% and 53% of the variation in SoFIE and LEED male earnings changes, and 54% and 26% for females. Female earnings are substantially more variable than male earnings, both in levels and in changes. Permanent and transitory earnings shocks are both substantially larger for women than for men, although permanent shocks are relatively more important for men.

The remainder of the paper is organised as follows. The next section reviews the measurement error literature pertaining to earnings. Section 3 discusses the data and sample selection to be used in the empirical analysis, and describes the possible sources of error associated with each earnings measure. Section 4 describes both the cross-sectional and longitudinal properties of the differences between SoFIE and LEED reported earnings. In section 5, we develop and estimate a model of earnings dynamics in the presence of possible measurement errors in both sources of data. The paper concludes with a discussion of the main findings in section 6.

2 Background literature

In this section we briefly discuss the literature on the dynamics of individual earnings, and the validation study literature on survey reported earnings.

2.1 Earnings dynamics

Friedman's permanent income hypothesis (PIH, Friedman, 1957) provides the conceptual motivation for much of the modelling of income and earnings processes, with its distinction between permanent and transitory components of income. See Meghir and Pistaferri (2011) for a detailed review of modeling incomes and earnings processes.

Estimates of individuals' income or earnings processes usually specify a regression to estimate the contribution of observable factors such as education and age or experience, together with an error components model to estimate the contributions of unobserved factors. Early statistical analyses typically specified the error as consisting of a time-constant individual-specific permanent component, and a low-order stationary autoregressive moving average (ARMA) transitory component (e.g. Lillard and Weiss, 1979, and Hause, 1980).

Seminal empirical analyses of the longitudinal structure of US male earnings by MaCurdy (1982) and Abowd and Card (1989) have resulted in the, now standard, characterisation of earnings as consisting of an individual-specific non-stationary random walk permanent component, a low-order stationary ARMA transitory component, and a purely transitory component which is typically interpreted to represent (classical) measurement errors (Meghir and Pistaferri, 2011). Such non-stationary representations of permanent components are preferred both conceptually, as they capture the PIH notion of adjustment to individuals' permanent income via shocks, and statistically, because the variance of individuals' earnings and income tend to increase over the life cycle, at least in the US and UK (Meghir and Pistaferri, 2011).

In our analysis, we will follow this literature and adopt such a specification for the true earnings process. The model will then be embellished to allow for reporting errors in the observed SoFIE and LEED earnings measures.

2.2 Validation studies of measurement error in earnings

Validation studies of reported earnings generally assume that the reported earnings are potentially measured with error, and that the second "validation" report accurately measures true earnings. Two recent exceptions are Kapteyn and Ypma (2007), and Abowd and Stinson (2013), who match survey information on individuals to admininistrative earnings records in Sweden and the US respectively. In each case the authors recognise that the administrative earnings may also include errors both due to the matching process and the administrative recording process, and develop methodologies that allow alternative assumptions on the reliability of the survey and administrative earnings.

Bound and Krueger (1991) analyse the properties of measurement error in reported earnings, using a sample of two matched years (1976 and 1977) from the March Current Population Survey (CPS) linked to the Social Security Administration (SSA) employer-reported Social Security earnings records. They consider alternative characterisations of measurement error, including the assumption of classical and mean-reverting measurement error.

Treating the SSA reports as true, Bound and Krueger show that, for males, the measurement error in CPS reported log(earnings) accounts for about 25% of earnings variation, is negatively correlated with the true earnings (correlation about -0.4) indicating mean-reversion in reported earnings, and is positively serially correlated (0.4).[1] These two results imply that the standard classical measurement error model is not appropriate for male earnings. In fact, the positive serial correlation implies that the effects of measurement error on differenced regression estimates are not as great as implied by classical measurement error. More detailed dynamic characterisation of the measurement error is not possible with only two observations per individual.

Bound et al. (1994) and Pischke (1995) each use data from a validation study conducted using the US Panel Study of Income Dynamics (PSID) questionnaire to workers at a single firm and matched to the firm's payroll records (PSIDVS), to analyse the dynamic properties of the measurement error in reported earnings and the implications for modeling earnings dynamics. The PSIDVS has payroll earnings over six years, 1981–1986, and worker reported earnings for 1982 and 1986 (as well as recall reports of earnings in the intervening years).

Similarly to Bound and Krueger, Bound et al. and Pischke treat the firm payroll reports as true earnings, and each conclude that errors are negatively correlated with true (i.e. payroll) earnings. For example, Pischke estimates that measurement error accounts for between 15% and 20% of reported log(earnings), and is negatively correlated with true earnings in 1982 (correlation -0.18) though weakly positively correlated in 1986. Pischke also estimates the correlation between measurement errors in 1982 and 1986 to be 0.094, which is too high to be consistent with an AR(1) process with correlation coefficient 0.4.[2]

Pischke then estimates a simple statistical model for true earnings and measurement error. The true earnings model consists of two components: a random-walk permanent

[1] The corresponding estimates for females are much smaller, -0.08 and 0.10 respectively. Bound and Krueger also find some evidence that the measurement error is correlated with covariates commonly included in earnings regression, which would cause bias in resulting earnings regression coefficients. However, on the basis of R^2's less than 0.1, they dismiss such correlation as being relatively weak.

[2] That is, 0.094 implies a first-order correlation of about 0.55. Conversely, a AR(1) correlation of 0.4 implies a fourth-order correlation of about 0.025.

component, and a pure-noise transitory component. The measurement error process consists of three components: first, a time-invariant person-specific component (unrelated to earnings); second, a component correlated with the transitory earnings shock; and third, a pure-noise classical measurement error component. Estimating this model, he finds, consistent with Bound and Krueger's results, that the second component is negatively correlated with transitory earnings. Pischke estimates that classical measurement error accounts for about 80% of total measurement error, and the other two components each account for about 10%.

In contrast to the studies discussed above, using survey data on individuals matched to administrative earnings records, both Kapteyn and Ypma (2007) and Abowd and Stinson (2013) allow for the administrative earnings to also be recorded with error. Kapteyn and Ypma (2007) analyse data from the Swedish administrative longitudinal database LINDA (Longitudinal Individual Data for Sweden), from which a sample was drawn for a validation survey in 2003. They focus on the survey and administrative reports of earnings, pensions and taxes. As well as measurement error in the validation survey responses, they allow for the possibility of measurement error in the administrative reports, assuming that any error will only be due to mismatch: with some probability an individual's record is mismatched, and drawn randomly from the LINDA population.

Consistent with the studies above, when assuming no measurement error in the LINDA administrative earnings, Kapteyn and Ypma (2007) find mean-reversion in the validation survey earnings responses. However, when they allow for errors due to mismatch, this finding largely disappears, and they conclude the survey reported measurement error is almost entirely classical.

Abowd and Stinson (2013) match individuals and their jobs from the US Survey of Income Program Participation (SIPP) to the Detailed Earnings Records (DER) data from the Social Security Administration.[3] Abowd and Stinson (2013) recognise that the admin-

[3]The SIPP are panel surveys of either 8 or 9 waves, conducted at 4-monthly intervals, and collect information pertaining to the 4 months since the previous survey. Gottschalk and Huynh (2010) also analysed the SIPP/DER matched data. Although they recognise that administrative data may not be error-free, and focus on the implications of differences between the sources for inequality measurement using SIPP, their analysis implicitly assumes that the DER reported earnings are true.

istrative earnings may also include errors due to both the matching and administrative recording processes, and develop a methodology that allows alternative assumptions about the relative ireliability of the survey and administrative earnings.

Abowd and Stinson (2013) matched both job-level and person-level reported earnings to DER records, and acknowledge three reasons the DER earnings may be measured with error: definitional differences with survey reports; recording errors in the administrative data; and errors in matching jobs and inidividuals between the SIPP and DER data sources. They develop a methodology to estimate and characterise the measurement error properties of reported earnings that does not rely on the assumption that the administrative earnings records are measured accurately. Assuming that DER reports are true results in an estimate of the reliability ratio of SIPP earnings of 0.78 in a person-sample with no imputed earnings. Conversely, assuming that SIPP reports are true, the estimated reliability ratio of DER earnings is 0.80. Giving equal weight to the alternative sources, the reliability ratios of SIPP and DER earnings are estimated as 0.94 and 0.95 respectively.

The data setup in Abowd and Stinson (2013) is similar to that in our study. In particular, the earnings information collected in SIPP pertains to an individual's jobs, which can then be aggregated to obtain the individual's (calendar year) annual earnings, and either job or individual-level earnings can then be matched to administrative data from the SSA's Detailed Earnings Record (DER). However, the DER job-earnings are only reported annually, compared to monthly LEED earnings reports. Thus, a degree of manipulation of both the survey collected information and administrative earnings is required to obtain comparable annual earnings from the SIPP and the DER. Analogous manipulations are required with the SoFIE and LEED earnings, however the monthly frequency of the LEED earnings data means it can be readily matched to the annual reference periods in SoFIE.

3 Data description and selection

The data used in our analysis consists of matched data from two sources within Statistics New Zealand's Integrated Data Infrastructure. Individuals are matched across the various data sources in the IDI by the date of birth, name and sex recorded in each data source.

The survey data we use is Statistics New Zealand's household panel Survey of Family, Income and Employment (SoFIE), which was conducted for 8-waves from 2002/3 until 2009/10.[4] The SoFIE survey instrument collected information on employment and earnings for each "job spell" covering the period from the previous survey to the current survey. Using this spell-level information, Statistics New Zealand derived an individual's income and earnings over an annual reference period. The annual reference period typically corresponds to the 12-months to the end of the calendar month prior to the first-wave's interview month. For example, for members of a household first interviewed in October 2002, the annual reference period is defined as the year to the end of September, in each wave. Thus, the calendar period for earnings in each wave spans 23 months – e.g. the first wave covers annual earnings periods from October 2001–September 2002 until September 2002–August 2003.

The annual earnings in SoFIE are derived from spell-level information, in contrast to many households panel surveys that ask respondents directly about their annual earnings.[5] In particular, the survey questionnaire administered to SoFIE respondents collected information on each of their job spells since the last survey. If there was a pay rate change during a job spell, the job spell was split so that each sub-spell had constant pay rate. The earnings contribution from each job is then derived based on its pay rate and the length of the job spell within the annual period. Each individual's annual earnings is then calculated by aggregating over these job earnings contributions.[6]

[4] SoFIE's survey years ran from October until September. We will refer to waves by the September calendar year of each wave – e.g. the first wave from October 2002 until September 2003 will be referred to as the "2003" wave, and the final wave from October 2009 to September 2010 as the "2010" wave.

[5] For example, both the US Panel Study of Income Dynamics (PSID), and the Australian Household Income and Labour Dynamics in Australia (HILDA) survey, collect annual income information across a range of income sources, including wage and salary employment, directly from respondents.

[6] Only individuals who completed the full SoFIE survey have earnings data, so we exclude those who did not complete the full survey: this applies particularly for those institutionalised, living overseas, or too sick to be interviewed.

The administrative earnings data we use is linked employer-employee earnings data (LEED). The raw LEED data is monthly earnings and other income, that has had tax withheld, reported in the Employer Monthly Schedules (EMS) filed by employers to Inland Revenue (IRD). The EMS covers the population of wage and salary employment earnings, as well as self-employment earnings and other monthly incomes which has had tax withheld at source.[7]

We first constructed an unbalanced panel over all 8 waves of individuals aged 20-64 from the SoFIE sample. We exclude 12 individuals (and 48 annual observations) with changing 'allocation months' for their annual reference period.[8] We also exclude 51 observations across 45 individuals with missing earnings data. This unbalanced SoFIE panel is then matched to the LEED data, and each individual's annual LEED earnings are constructed by aggregating their monthly earnings over their SoFIE annual reference periods. We retain only those SoFIE individuals who could be matched to the IDI spine (97% of the full sample). Throughout the paper, we use SoFIE and LEED nominal annual earnings values (i.e. not adjusted for inflation).

We then sequentially subsample the full unbalanced panel of 20-64 year-olds using three criteria. First, because the LEED data includes a self-selected subsample of self-employment earnings, we exclude individual-year observations if they report any self-employment activity in that wave, regardless of their other employment. Second, we select the balanced panel of individuals aged 20-64 throughout the 8 waves, who never have self-employment as their main source of employment earnings. Third, we select the balanced panel of individuals with reported earnings from both SoFIE and LEED, and no self-employment, in each year.

Table 1 summarises the characteristics of these four samples, as well as the unmatched SoFIE subsample. Unmatched individuals are disproportionately female, Asian or Pasific Islander and less likely European, are more likely to have only high school qualifications,

[7]The self-employment earnings included in the EMS is a non-random subset of all self-employment earnings. Other monthly withholding income in the EMS include payments associated with Work and Income benefits, New Zealand Superannuation, earnings-related accident compensation (ACC), Student Allowances, and Paid Parental Leave.

[8]An individual's allocation month changes when they move from one SoFIE household into another that has a different allocation month.

are less likely to have vocational qualifications, and have lower employment rates and earnings levels.

Within the matched sample, the successive subsample selection criteria result in the exclusion of 9% individuals and 16% observations due to self-employment; 68% of individuals and 42% of observations due to the balanced panel requirement; and 35% of individuals and observations associated with both SoFIE and LEED earnings in each year. Thus, the final sample which is used for our analysis of earnings dynamics, accounts for 19% of the full sample individuals and 31% of all annual observations.

The sample characteristics across the four samples follow broadly similar patterns. Women are less likely to be either self-employed or employed, and are more likely to be observed in each wave of the SoFIE panel. Similarly, Europeans are more likely to be self-employed, appear in the balanced panel, and work in each wave than other ethnic groups. Also, and probably not surprisingly, employment as measured in SoFIE, the number of months with earnings in LEED, and measured earnings from both sources, tend to be higher in the more selective samples. Finally, the average difference between SoFIE and LEED reported earnings is greater in the balanced panel than the unbalanced panel samples (about 4% in samples 3 and 4, versus 2% in sample 1 and 2) but less variable, reflected by both the standard deviations and the average absolute differences being lower.

3.1 Sources of error in reported earnings

The two sources of earnings data we use are expected to have alternative and various sources of measurement error. Errors in the derived annual earnings recorded in SoFIE may be due to three factors. First, from errors in respondents' reporting the existence or duration of job spells. Second, from errors in their reporting of the wage or salary rate associated with a job spell. Third, from the derivation of annual earnings based on the spell-level information collected. The first and second reflect errors in respondents' recall or accuracy, while the third reflects any errors in the derivation algorithm used to estimate annual earnings from job-spell information that the survey instrument collected.

The sources of errors in the annual earnings recorded in LEED most likely are quite different to those recorded in SoFIE. First, there may be differences in coverage, such as self-employment earnings, or informal sector (under-the-table) earnings, that are not included in the EMS forms.[9] Second, there is likely to be error in the matching of data from different sources in the IDI, resulting in some false earnings matches. Third, there may be some recording errors in the administrative data, either associated with the amount of earnings or in the timing of earnings recorded through the EMS returns.[10]

4 SoFIE versus LEED earnings comparisons

4.1 Cross-sectional earnings comparison

We begin by summarising some descriptive patterns of the earnings reported in each of SoFIE and LEED. Table 2 summarises the cross-sectional concordance between the extensive margins of earnings reported in the two sources for the alternative samples described above. As expected, the presence of self-employed observations in the full sample results in a lower incidence of LEED earnings (74% in the full sample versus 81% in the sample excluding self-employed observations), and of SoFIE earnings (72% versus 81%). The fractions of observations reporting positive earnings from either source when the self-employed are excluded is 81%, and about 83% in the balanced panel sample. There is about 95% agreement between the two sources on the presence of earnings, and about 80% agreement on the absence of earnings.

Table 3 summarises the SoFIE and LEED earnings for the subsamples stratified by the extensive margin concordance described in Table 2. For each sample, reported earnings are both substantially higher on average and less variable among observations with both SoFIE and LEED reported earnings than among observations with reported earnings from only one source. This pattern is consistent with observed reporting and matching being more prevalent the greater the level of earnings.

[9]Such informal earnings may or may not be reported by survey respondents.

[10]For example, there may be a delay in the payment and recording of earnings in the EMS relative to when the work was done.

Figure 1 and Figure 2 present the distributions of SoFIE and LEED reported annual earnings, together with the log-difference between these measures, for samples 2 and 4 respectively. First, the sample 2 distributions show a lot more mass at low earnings levels than sample 4, reflecting that those who have earnings in each year have a stronger attachment to employment and hence higher earnings. Second, the two SoFIE earnings distributions also contain more spikes at salient levels (e.g. $10K values) than the LEED earnings distributions, perhaps reflecting a tendency for individuals to report rounded earnings values. Third, the distributions of log-differences between SoFIE and LEED earnings are comparatively bell-shaped about zero, although with thicker tails than associated with a normal distribution.

Table 4 summarises the differences between the reported SoFIE and LEED log(earnings) for annual observations with both reports. For the two unbalanced samples, reported earnings in SoFIE are about 2% lower on average than earnings recorded in LEED, and the standard deviations of the log-differences are 0.56–0.58. In the balanced panel samples, the average log-differences are larger (-0.04) but less variable (standard deviations of 0.49 in Sample 2 and and 0.38 for Sample 4). Also, although almost no observation reports exactly the same SoFIE and LEED earnings, about 10% of observations have differences less than 1%, between one-third and 40% have differences less than 5%, and 50-60% have differences less than 10%.

Next, to examine other correlates of the difference in the two reported earnings, we regress the log-difference on individuals' demographic and other characteristics. The results are reported in Table 5 for the three samples that exclude self-employed observations. Although many of the coefficients are statistically significant, they are generally modest in size. Reported earnings are lower in SoFIE than LEED for Pacific Island, Asian, and Other ethnicities, and these characteristics are associated with higher absolute log(earnings) differences. Observations with more months of LEED earnings tend to under-report earnings in SoFIE relative to LEED, but have lower absolute log(earnings) differences.

4.2 Classical measurement error in SoFIE

The simplest and most restrictive assumption on the errors between the SoFIE and LEED reported earnings, is that the LEED earnings accurately measure true annual earnings (Y^*), and the SoFIE earnings are reported with purely random errors. That is, denoting Y_{Lit} as log(LEED earnings) of individual-i in year-t and Y_{Sit} as log(SoFIE earnings), the classical measurement error model is

$$\begin{aligned} &Y_{Lit} = Y^*_{it}, \\ &Y_{Sit} = Y^*_{it} + \epsilon_{it}, \epsilon_{it} \sim iid(0, \sigma^2_\epsilon), \end{aligned} \tag{1}$$

and the difference between the SoFIE and LEED reports is simply the measurement error in SoFIE earnings: $\epsilon_{it} = Y_{Sit} - Y_{Lit}$.

The assumption of classical errors has several strong implications. First, it implies that the differences between SoFIE and LEED reports should be serially uncorrelated, and uncorrelated with the LEED reports and any observed covariates, and we explore each of these implications later. Second, it implies that in a regression of Y_S on Y_L, the coefficient on Y_L will be close to 1, while in the reverse regression, the coefficient on Y_S will be attenuated towards zero. To see this, consider the two regressions:

$$\begin{aligned} &Y_{Sit} = \alpha_0 + \alpha_1.Y_{Lit} + u_{Sit}, \\ &Y_{Lit} = \delta_0 + \delta_1.Y_{Sit} + u_{Lit}. \end{aligned} \tag{2}$$

In the first regression, $plim(\hat{\alpha}_1) = Cov(Y_{Lit}, Y_{Sit})/Var(Y_{Lit}) = \sigma^2_{Y^*}/\sigma^2_{Y^*} = 1$, while in the second regression $plim(\hat{\delta}_1) = Cov(Y_{Lit}, Y_{Sit})/Var(Y_{Sit}) = \sigma^2_{Y^*}/(\sigma^2_{Y^*} + \sigma^2_\epsilon) < 1$, where $\sigma^2_{Y^*}$ and σ^2_ϵ are the variances of true log(earnings) and measurement error respectively. In this context, $\sigma^2_{Y^*}/(\sigma^2_{Y^*} + \sigma^2_\epsilon)$ is also referred to as the signal-to-total variability, or the reliability ratio, of Y_S.

To evaluate this hypothesis, we present the estimates for each of these regressions in Table 6. The coefficients in the regressions of Y_{Sit} on Y_{Lit} range from 0.88 to 0.91 across the four samples, and are each statistically significantly lower then 1. In a classical error context, this rejects the assumption of no measurement error in the LEED reported earnings. The coefficients in the reverse regression of Y_{Lit} on Y_{Sit} range from 0.82 to 0.85, and also reject the hypothesis of no measurement error in log(SoFIE earnings). In a classical error context, these estimates imply that 9–13% of the variation in log(LEED earnings), and 15–18% of the variation in log(SoFIE earnings) is due to measurement error. Thus the estimated statistical reliability of LEED earnings (87–91%) is higher than that of SoFIE earnings (82–85%).

We next examine the relationship between the errors between the two reports and LEED earnings. In the third panel of Table 6 we report estimates from regressions of the difference in log(earnings) ($DY_{it} = Y_{Sit} - Y_{Lit}$) on individuals' average LEED log(earnings) over the period (Y_{Li}) and the year-specific deviation from this average ($Y_{Lit} - Y_{Li}$):

$$DY_{it} = \alpha + \beta.Y_{Li} + \delta.(Y_{Lit} - Y_{Li}) + u_{it}. \tag{3}$$

The differences in reported log(earnings) are negatively correlated both with individuals' average LEED earnings and their annual deviations, suggesting measurement errors are mean reverting with respect to both permanent earnings differences across individuals and also their transitory earnings. The coefficient on annual deviations is roughly constant across the four samples, suggesting individuals under report about 20% of transitory earnings; while the coefficient on average log(earnings) is higher in the unbalanced panels (-0.1) than in the balanced panel of earners (-0.05). This suggests the under reporting of persistent differences is lower than the under reporting of transitory differences, and also less important for those with persistent employment.

4.3 Panel earnings comparison

We next analyse the longitudinal properties of differences between SoFIE and LEED earnings. We begin by describing the patterns of SoFIE and LEED extensive margin agreements. Table 7 documents the transition matrices of year-to-year extensive margin outcomes for samples 1–3. The patterns show a degree of persistence in the cross sectional concordance between SoFIE and LEED reports, which reflects partly the persistence in employment outcomes, and partly the reporting patterns conditional on employment. There are particularly strong persistence in reporting of earnings in both sources in consecutive years, consistent with high employment persistence. Similarly null earnings reports in both sources are highly correlated. Of greater interest is that individuals who have SoFIE but not LEED reported earnings in one year are about 75% likely to have the same pattern in the following year; and this is stronger for the samples excluding self-employed workers. Also, when self-employed are excluded, those with LEED but not SoFIE earnings in one year have about 35% chance of having the same in the following year, and a similar chance of having positive earnings reported in both sources.

In Table 8 we document the auto-covariance matrices of the conditional differences in SoFIE and LEED reported log(earnings) over the period. In order to abstract from possible selection effects associated with unbalanced panel samples, for this analysis we focus on the two balanced panel samples (i.e. samples 3 and 4).[11] To allow for possible variation over time in the average difference in reported earnings, we calculate the variances and covariances relative to year-specific mean differences, and present these means at the bottom of each panel of the table. For sample 3, which is unbalanced in terms of observed earnings, the auto-covariance structure is based on samples of log(earnings) errors for each pair of years. The patterns across the two samples are broadly similar. The variances of the differences between SoFIE and LEED log(earnings) are higher in sample 3 (from 0.20 to 0.29) than sample 4 (0.11 – 0.20). Although the average differences between SoFIE and LEED earnings are negative across both samples and years, they are slightly smaller in sample 3 than sample 4, suggesting greater variability in reported earning differences for individuals with intermittent employment over the period.

An additional implication of the classical measurement error model outlined in section 4.2 is that the autocovariance structure of the T-vector of errors ($\hat{\epsilon}_i$) will be diagonal with σ^2_ϵ on the diagonal. The auto-correlation patterns in Table 8 are clearly inconsistent with this prediction, and suggest that the errors between the SoFIE and LEED reported

[11] The results based on the unbalanced samples are substantively similar, although with greater variability.

earnings include both persistent and transitory components. The first-order correlations are on the order of 0.25–0.35, while the higher order correlations are close to 0.1. In fact, the declining autocorrelation patterns across the two samples suggest the errors include transitory components that persist for 1-2 lags, as well as permanent components that persist longer, accounting for about 10% of the variance of the difference in reported earnings. We will draw on these patterns, as well as results in the literature, to help inform the nature of measurement errors that we allow in the next subsection.

Another feature of Table 8, particularly for the balanced panel of earnings, is that the variances are much higher in the first and last waves. We suspect this has to do with the selection criteria for the balanced panel: the end years likely have a larger fraction of part-year earners who are either entering or leaving employment, with greater associated variability in the difference in reported earnings.[12] Similar end-year differences are apparent in the variance of earnings changes that we discuss in the next section.

5 Modeling earning dynamics

We now consider modelling the dynamics of individuals' earnings in the context of mismeasured reported earnings. In order to abstract from the additional difficulty of modeling individuals' employment decisions in the presence of measurement error, we focus on the balanced panel of individuals with both SoFIE and LEED earnings reported in each year.

5.1 A model of earnings dynamics and measurement error

In this section, we discuss the structure of measurement error that we will attempt to assess. We relax the assumption that the administrative source of earnings reported in LEED is measured without error, and develop a specification of measurement error in each of the SoFIE and LEED reported earnings within the context of a dynamic model of earnings.

[12]For example, individuals entering employment in wave-1 would be excluded if the panel was extended back by one year; similarly, those leaving employment in wave-8 would be excluded in the panel was extended forward by one year.

The literature on validation studies of survey reported earnings concludes that the classical measurement error model is too restrictive. For example, both Bound and Krueger (1991) and Pischke (1995) found evidence of serial correlation in the measurement error in PSID reported earnings;[13] and of mean-reversion in the measurement error in PSID reported earnings. In this case, we assume that $E(\epsilon_{it}) = 0$, but allow that $Corr(\epsilon_{it}, Y_{it}^*) \neq 0$: mean reversion implies that $Corr(\epsilon_{it}, Y_{it}^*) < 0$.[14] The interpretation of such non-classical measurement errors is usually that respondents under-report transitory earnings shocks due to memory lapses.

In contrast to errors in survey meaures, errors in administrative earnings reports are expected to be due to either mis-matching of an individual's jobs or random mis-coding of their earnings. The latter source is likely to generate classical errors, while we interpret the former as possibly having a person-specific and a random component.[15]

We begin by specifying the dynamics of true earnings. Following the literature (e.g. Abowd and Card, 1989, Meghir and Pistaferri, 2004), we assume individual-i's true log(earnings) in year-t consist of a permanent random walk component plus a transitory MA(1) component:[16]

$$\begin{aligned} Y_{it}^* &= \alpha_{it} + u_{it}, \\ \alpha_{it} &= \alpha_{it-1} + \eta_{it}, \\ u_{it} &= \omega_{it} + \theta\omega_{it-1}, \end{aligned} \tag{4}$$

where $\eta_{it} \sim iid(0, \sigma_\eta^2)$, and $\omega_{it} \sim iid(0, \sigma_\omega^2)$.

Second, broadly consistent with Bound and Krueger (1991), Pischke (1995), and the patterns in Table 8, we assume that the measurement error in individual-i's SoFIE re-

[13] This implies $Corr(\epsilon_{it}, \epsilon_{is}) \neq 0, s \neq t$. The pattern of autocorrelations in Table 8 is also consistent with serially correlated errors.

[14] The results in Table 6 suggest that both $Corr(\epsilon_{it}, Y_i^*) < 0$ and $Corr(\epsilon_{it}, Y_{it}^* - Y_i^*) < 0$, where Y_i^* is individual-i's average earnings over the period.

[15] To the extent that mis-matches are job-specific, this source may generate a person-job persistent component of error. If so, the measurement error may be serially correlated, but is unlikely to be mean reverting.

[16] Note that most empirical analyses of earning dynamics include a purely transitory component of earnings; however, this is generally assumed to be due to the presence of measurement error in survey reports, and is not separately identified from the MA component (see Meghir and Pistaferri, 2011).

ported earnings consists of a person-specific component, components related to their permanent earnings shock and their transitory earnings, and a classical error component:

$$\epsilon_{Sit} = \lambda_{Si} + \delta_{1S}\eta_{it} + \delta_{2S}u_{it} + \nu_{Sit}, \tag{5}$$

where $\lambda_{Si} \sim iid(0, \sigma^2_{S\lambda})$ and $\nu_{Sit} \sim iid(0, \sigma^2_{S\nu})$. Mean-reverting errors imply δ_{1S} and δ_{2S} are negative. This implies that the individual's SoFIE reported earnings are:

$$Y_{Sit} = Y^*_{it} + \epsilon_{Sit} = \alpha_{it} + \lambda_{Si} + \delta_{1S}\eta_{it} + (1 + \delta_{2S})u_{it} + \nu_{Sit}. \tag{6}$$

Third, we assume that the measurement error in individual-i's LEED reported earnings consists of a person-specific component and a classical error component:

$$\epsilon_{Lit} = \lambda_{Li} + \nu_{Lit}, \tag{7}$$

where $\lambda_{Li} \sim iid(0, \sigma^2_{L\lambda})$ and $\nu_{Lit} \sim iid(0, \sigma^2_{L\nu})$. Thus individual-$i$'s LEED reported earnings are:

$$Y_{Lit} = Y^*_{it} + \epsilon_{Lit} = \alpha_{it} + \lambda_{Li} + u_{it} + \nu_{Lit}. \tag{8}$$

In order to abstract from the initial conditions associated with individual i's permanent earnings component (α_{i0}), we estimate the model using the first differences of SoFIE and LEED earnings. This also has the effect of eliminating the person-specific components of error (λ_{Si} and λ_{Li}), so their contributions are not identified. In particular, equations (4), (6) and (8) imply:

$$\begin{aligned} \Delta Y_{Sit} &= (1 + \delta_{1S})\eta_{it} + (1 + \delta_{2S})\Delta u_{it} + \Delta\nu_{Sit}, \\ \Delta Y_{Lit} &= \eta_{it} + \Delta u_{it} + \Delta\nu_{Lit}. \end{aligned} \tag{9}$$

The vector of parameters of interest in the model is $(\sigma^2_\eta, \sigma^2_\omega, \theta, \delta_{1S}, \delta_{2S}, \sigma^2_{S\nu}, \sigma^2_{L\nu})$. These parameters are identified from the auto-covariances and cross-covariances of ΔY_{Sit} and

ΔY_{Lit}: the model predicted variances and covariances are presented in the appendix. One implication of the model is that all auto- and cross-covariances of ΔY_{Sit} and ΔY_{Lit} beyond second-order are zero.

We estimate the model using minimum distance estimation methods (Abowd and Card, 1989; Chamberlain, 1984). This involves choosing the vector of parameter estimates to minimise the weighted sum of squared differences between the empirical and model-predicted second moments. Because of finite sample bias associated with the second and fourth moments being correlated (Altonji and Segal, 1996), we weight using the diagnonal matrix with inverse sampling variances of the empirical moments on the diagonal instead of the optimal weight matrix which also includes the off-diagonal sampling covariances.

5.2 Estimation results

We first present the empirical covariance matrix of $(\Delta Y_{Sit}, \Delta Y_{Lit})$ in Table 9 for males, and summarised for males and females in Table 10.[17] To allow for wage inflation and other aggregate affects on earnings over time, the variances and covariances are calculated relative to year-specific mean earnings changes, which are reported at the bottom of the table. The variances of SoFIE earnings changes are substantially larger than for LEED changes, which suggests a greater degree of random measurement error in SoFIE earnings.[18] Consistent with the patterns of autocorrelations in the log differences between SoFIE and LEED reports and much of the literature on earnings dynamics, and in line with the model predictions in section (5.1), the first- and second-lagged auto-covariances of SoFIE and LEED earnings changes are generally statistically significantly different from zero, while all the higher order covariances are small and individually statistically insignficantly different from zero. The first-order auto-correlations are typically between -0.2 and -0.3, and the second order auto-correlations are also negative and generally smaller than 0.1 in magnitude.

[17] The equivalent covariance structure for females is presented in appendix Table A1.

[18] As discussed in section 4.3, the variances of each measure's change in earnings is much greater in the end years than the intermediate years of the panel. As well as greater variance of earnings change in these years, the mean earnings growth is generally stronger between waves 1 and 2 (0.09 for SoFIE earnings, and 0.12 for LEED earnings), and much weaker between waves 7 and 8 (-0.02 in SoFIE and -0.01 in LEED), consistent with end-year entry and exit patterns respectively.

The contemporaneous cross-covariances between the changes in SoFIE and LEED earnings are statistically significant, with implied correlations of 0.40 on average for males and 0.57 for females. In contrast to the auto-covariances, most of the first-order, and all of the higher-order, cross-covariances are statistically insignificant. Interestingly, the first-order correlations associated with LEED leading SoFIE, $Cov(\Delta Y_{Sit}, \Delta Y_{Lit-1})$, tend to be greater than for SoFIE leading LEED, $Cov(\Delta Y_{Sit-1}, \Delta Y_{Lit})$: typically on the order of (-0.1,-0.05) for the former, and (-0.05,0) for the latter.

We next present estimates of alternative specifications of the model in equations (4)–(9). The results are contained in Table 11, for models estimated separately for males and females. To provide a baseline comparison with literature that assumes that the validated administrative earnings are reported without error, we first estimate models that has this condition. The estimates, presented in the first column for males and females, are similar to findings in the literature. In particular, there is evidence of positively correlated transitory components of earnings, with the measurement error in SoFIE earnings being insignificantly correlated with permanent shocks and more strongly mean-reverting with respect to the transitory component of earnings. Consistent with Bound and Krueger (1991), we estimate stronger mean reversion in male than in female earnings, but more transitory and classical measurement error in female earnings.

In column (2) we present estimates of the model allowing for measurement error in the LEED earnings. First, there is evidence of significant measurement error in LEED earnings in this model: the estimated variance of the measurement error is almost the same for males and females (0.023 and 0.25 respectively). The results imply substantially less measurement error in LEED than in SoFIE earnings: the estimated variance of LEED errors is about one-half the variance of classical measurement error in SoFIE earnings for males, and about one-third for females.

Second, allowing for measurement error in LEED earnings, the result that SoFIE measurement error is negatively correlated with transitory earnings is overturned, with each of the estimated δ_{2S} parameters being positive, although imprecisely estimated. However, we do estimate small and insignificant negative correlations between SoFIE measurement error with individuals' permanent earnings shocks (δ_{1S}) for each sample. This result that mean reversion in survey earnings is not robust to the presence of measurement error in administrative data is consistent with Kapteyn and Ypma (2007) based on a different approach.

We present two sets of formal goodness-of-fit (GOF) statistics for each model in Table 11. The is first based on the full set of empirical covariances (GOF1), and the second is based on just the non-zero predicted covariances (GOF2). Although the second model fits salient aspects of the empirical covariance matrix presented in Table 9, neither of the models provides an adequate statistical fit to the structure as judged by the GOF statistics. Both models fit relatively better for males than females, while excluding the zero-predicted moments has a larger effect for females. One possible issue is that both models restrict the earnings and error process to be stationary over the period, while there is evidence of time varying variances and covariances. As discussed above, the first and last year variances are noticeably higher, perhaps due to these end years including individuals with more variable earnings associated with moving in or out of employment, who would have been excluded if the sample period was extended in either direction.

To account for this source of non-stationarity, we next estimate a model that allows for separate end-year variances in the classical measurement error components of SoFIE earnings ($\sigma^2_{S\nu 0}$) and LEED earnings ($\sigma^2_{L\nu 0}$). The results of this model are in presented in column (3). The estimated end-year variances for the measurement errors in LEED are nearly three times the the variances of the other years, again with similar magnitudes for males and females. For SoFIE errors, the end-year variance for males is also much larger (about 2.5 times) than the variance for other years, but for females these variances are of similar magnitude. The decrease in the GOF statistics for this specification imply a substantial improvement in the fit of the model, especially for females. However, it has almost no effect on the other parameter estimates in the model, especially those concerned with true earnings.

The final model, presented in column (4), extends this idea and allows wave-specific classical measurement error variances in each of SoFIE and LEED earnings, which will allow the variances and first-order covariances to vary over time. Although the model's statistical adequacy is still rejected by the formal GOF statistics, the large falls in the GOF statistics shown in the table indicate it provides a significantly better fit to the empirical moments. Perhaps more substantively, the other parameter estimates are almost unchanged as a result of this relaxation of the model.

We have also estimated baseline earnings dynamics models using just SoFIE or LEED earnings data separately, and ignoring measurement errors, and also a joint model that allows for classical measurement errors in each measure of earnings. The results are presented in appendix Table A2. First, using the separate earnings reports results in quite different estimates of the permanent shocks: the estimated variance is much larger based on SoFIE than on LEED reported earnings, with the estimates for both males and females sandwiching the estimates shown in Table 11.

Second, the estimated variances of the transitory earnings shocks in Table A2 are much larger than in Table 11, and the θ-coefficients that determine the persistence of the transitory shocks are much lower. This is because it is not possible to separately identify the transitory earnings effects from measurement error using a single source of earnings. As a result, random measurement errors will inflate the estimated transitory shocks, and reduce the estimated persistence.

Third, the estimates of the model that allows only classical measurement errors in each of SoFIE and LEED, based on both sources of earnings data, are quite similar to those for the models that also allow SoFIE errors to have non-classical components. This isn't surprising since the estimated δ parameters in those models are statistically insignficant. However, the GOF statistics suggest this model provides a noticeably worse fit to the moments, especially for females.

The predicted variance-covariance matrix of $(\Delta Y_{Sit}, \Delta Y_{Lit})$, based on specification (4), together with the differences between the empirical and predicted moments, are presented in Table 12 (the equivalent predictions for females are presented in Table A3). Although these models are rejected on the basis of the formal GOF criteria, there are no obvious patterns of misfit apparent in the predicted moments. Also, except for model (4) providing a noticeably better fit to the variances, the simpler model (2) specification provides broadly comparable predictions. Given this, and that the core model parameters are largely unaffected by relaxing the stationarity of the classical error variances, we will use this simpler model in the next section for discussing the implications of this analysis for understanding individuals' earnings inequality.

5.3 Implications for earnings dynamics and inequality

In this section we discuss the implications of the earnings dynamics model for the extent and persistence of inequality in true earnings. Because the permanent components of measurement error are not separately identified in the model, the model does not directly inform the level of earnings inequality. However, we can address the source and impact of earnings shocks as measured by the variance of changes in log(earnings). A summary of the results are presented in Table 13, based on the estimates of model (2) in Table 11.

First, measurement errors in both SoFIE and LEED reported earnings account for substantial proportions of the variances of reported earnings changes. In particular, the predicted variance of true log(earnings) changes is 0.042 for males, which accounts for only 29% and 47% of the predicted variances of change in SoFIE (0.144) and LEED (0.089) reported earnings respectively. For females, the predicted variance of true log(earnings) changes is 0.139, which accounts for 46% and 74% of the predicted variances of SoFIE (0.304) and LEED (0.189) reported earnings changes respectively.

Second, female log(earnings) changes are substantially more variable than males. For example, the variances of observed log(earnings) changes are roughly twice for females compared to males: 0.304 versus 0.144 for SoFIE reports, and 0.189 versus 0.089 for LEED. In fact, the female variance of true earnings changes is more than three times larger than for males: 0.139 versus 0.042. This difference is due both to larger permanent shocks (0.086 versus 0.034), transitory shocks (0.035 versus 0.005) which are also (slightly) more persistent for females (θ=0.46 versus 0.40 for males).

Third, although the permanent components of measurement errors in the model are not identified, we are able to bound their effects. Equations (6) and (8) imply:

$$DY_{it} = Y_{Sit} - Y_{Lit} = \delta_{1S}\eta_{it} + \delta_{2S}u_{it} + (\lambda_{Si} - \lambda_{Li}) + (\nu_{Sit} - \nu_{Lit}). \tag{10}$$

This implies the auto-covariance in DY_{it} equals $Var(\lambda_{Si} - \lambda_{Li})$ beyond first-order. As discussed above, the auto-correlations in Table 8 suggest that this variance accounts for about 10% of the $Var(DY_{it})$.[19] Assuming the permanent components of reporting errors (λ_{Si} and λ_{Li}) are independent (or at least not negatively correlated), then the combined and separate effects of $\sigma^2_{\lambda Si}$ and $\sigma^2_{\lambda Li}$ are less than 10% of $Var(DY_{it})$. This provides upper bounds for $\sigma^2_{\lambda Si}$ and $\sigma^2_{\lambda Li}$ of about 0.012 for males and 0.017 for females.

Together with the empirical variances of SoFIE and LEED log(earnings), these bounds can help inform the discussion of the extent of measurement error in the level of earnings, and their effects on inequality. For example, using the empirical variances of observed SoFIE and LEED log(earnings) of 0.164 and 0.135 respectively for males, the estimates above imply the maximal measurement error contributions are 0.065 and 0.035, giving lower bound estimates of the variances of true log(earnings) of 0.10 (consistent across the SoFIE and LEED reports). Similarly, the variances of SoFIE and LEED log(earnings) for females are 0.424 and 0.352, with estimated maximal measurement error contributions of 0.104 and 0.042, implying estimated variances of true log(earnings) of 0.31–0.32.[20]

Finally, using these estimates of the variance of true earnings and the estimates of the components of earnings, suggests that transitory variation accounts for a relatively trivial fraction of the variance of male earnings (about 6%), and about 13-14% of female earnings.

[19] Although $Var(DY_{it})$ differs for males (0.12 on average) and females (0.17 average), the correlations are quite similar.

[20] Note, these estimates imply reliability ratios for males of only 61% for SoFIE and 74% for LEED, which are much lower than simple empirical estimates of 80% and 88% respectively. For females, the implied reliability ratios are 75% for SoFIE and 88% for LEED, are somewhat closer to the empirical estimates of 83% and 91%.

6 Concluding discussion

This paper has analysed the measurement error and dynamic properties of individuals' earnings using a longitudinal sample of two earnings reports: the first dervied from individuals' reported job spells in the SoFIE longitudinal panel survey, and the second dervied from administrative LEED earnings for the matched SoFIE sample. The analysis provides several conclusions.

First, in a cross-sectional context, the joint hypothesis that SoFIE earnings are reported with classical measurement error and the administrative LEED earnings are recorded without error is rejected. Under the assumption that LEED earnings are correct, we estimate similar mean-reverting patterns in SoFIE earnings to that found in the validation literature. In particular, differences between SoFIE and LEED earnings are negatively correlated with both persistent differences and transitory changes in individuals' earnings. Within a classical measurement error context, we conclude that individual earnings are more reliably reported in LEED than in SoFIE, with reliability ratios about 90% and 85% respectively.

Second, examining the longitudinal properties of the difference between SoFIE and LEED earnings for individuals further confirms the non-classical nature of the errors. In particular, we find that the covariance structure is characterised by both persistent and serially correlated transitory components, and suggest a simple stylised model would include a person specific permanent component of error plus a low-order ARMA component.

Third, we build on the empirical characteristics of the differences between SoFIE and LEED earnings, together with findings from the literature on individuals' true earnings dynamics, to formulate a model for the SoFIE and LEED reported earnings. In line with the literature, we find that the measurement error in SoFIE earnings is mean-reverting within this formulation when the LEED earnings are assumed to be true. However, as with Kapteyn and Ypma (2007), when we allow for errors in LEED earnings this result goes away. In fact, we conclude that each source of earnings is largely characterised by classical measurement error and possibly a person-specific permanent component of error.

Finally, the estimated model implies that measurement errors accounts for over half of the variance of change in male LEED earnings and about 70% of the change in SoFIE earnings; for females, about one-quarter and one-half of the variance of earnings changes in LEED and SoFIE are due to measurement errors. True Female earnings, as well as earnings changes, are about three times more variable than for males. The differences are due to both greater permanent and transitory shocks, although permanent shocks are relatively more important in male earnings, accounting for 94% of differences and about 80% of changes, compared to 86% and 60% for females.

References

Abowd, J. M. and D. Card (1989). On the covariance structure of earnings and hours changes. *Econometrica 57*(2), 411–445.

Abowd, J. M. and M. H. Stinson (2013). Estimating measurement error in annual job earnings: A comparison of survey and administrative data. *Review of Economics and Statistics 95*(5), 1451–1467.

Altonji, J. G. and L. M. Segal (1996). Small-sample bias in gmm estimation of covariance structures. *Journal of Business & Economic Statistics 14*(3), 353–366.

Bound, J., C. Brown, G. J. Duncan, and W. L. Rodgers (1994). Evidence on the validity of cross-sectional and longitudinal labor market data. *Journal of Labor Economics*, 345–368.

Bound, J., C. Brown, and N. Mathiowetz (2001). Measurement error in survey data. *Handbook of econometrics 5*, 3705–3843.

Bound, J. and A. B. Krueger (1991). The extent of measurement error in longitudinal earnings data: Do two wrongs make a right? *Journal of Labor Economics*, 1–24.

Chamberlain, G. (1984). Panel data. *Handbook of econometrics 2*, 1247–1318.

Friedman, M. (1957). The permanent income hypothesis. In *A theory of the consumption function*, pp. 20–37. Princeton University Press.

Gottschalk, P. and M. Huynh (2010). Are earnings inequality and mobility overstated? the impact of nonclassical measurement error. *The Review of Economics and Statistics 92*(2), 302–315.

Hause, J. C. (1980). The fine structure of earnings and the on-the-job training hypothesis. *Econometrica: Journal of the Econometric Society*, 1013–1029.

Hyslop, D. R. (2001). Rising us earnings inequality and family labor supply: The covariance structure of intrafamily earnings. *American Economic Review*, 755–777.

Kapteyn, A. and J. Y. Ypma (2007). Measurement error and misclassification: A comparison of survey and administrative data. *Journal of Labor Economics 25*(3), 513–551.

Lillard, L. A. and Y. Weiss (1979). Components of variation in panel earnings data: American scientists 1960-70. *Econometrica: Journal of the Econometric Society*, 437–454.

MaCurdy, T. E. (1982). The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of econometrics 18*(1), 83–114.

Meghir, C. and L. Pistaferri (2004). Income variance dynamics and heterogeneity. *Econometrica 72*(1), 1–32.

Meghir, C. and L. Pistaferri (2011). Earnings, consumption and life cycle choices. *Handbook of Labor Economics 4*, 773–854.

Pischke, J.-S. (1995). Measurement error and earnings dynamics: Some estimates from the psid validation study. *Journal of Business & Economic Statistics 13*(3), 305–314.

Appendix A Model predicted covariances

In this appendix we present the variances and covariances of the changes in SoFIE and LEED log(earnings) in equations (9), from the earnings model described by equations (4), (6) and (8) in section 5.1. In particular, the variances and covariances are:

$$Var(\Delta Y_{Sit}) = (1+\delta_{1S})^2\sigma_\eta^2 + (1+\delta_{2S})^2\sigma_{\Delta u}^2 + 2\sigma_{S\nu}^2,$$

$$Cov(\Delta Y_{Sit}, \Delta Y_{Sit-1}) = (1+\delta_{2S})^2 Cov(\Delta u_{it}, \Delta u_{it-1}) - \sigma_{S\nu}^2,$$

$$Cov(\Delta Y_{Sit}, \Delta Y_{Sit-2}) = (1+\delta_{2S})^2 Cov(\Delta u_{it}, \Delta u_{it-2}),$$

$$Cov(\Delta Y_{Sit}, \Delta Y_{Sit-k}) = 0, k > 2,$$

$$Var(\Delta Y_{Lit}) = \sigma_\eta^2 + \sigma_{\Delta u}^2 + 2\sigma_{L\nu}^2,$$

$$Cov(\Delta Y_{Lit}, \Delta Y_{Lit-1}) = Cov(\Delta u_{it}, \Delta u_{it-1}) - \sigma_{L\nu}^2,$$

$$Cov(\Delta Y_{Lit}, \Delta Y_{Lit-2}) = Cov(\Delta u_{it}, \Delta u_{it-2}),$$

$$Cov(\Delta Y_{Lit}, \Delta Y_{Lit-k}) = 0, k > 2,$$

$$Cov(\Delta Y_{Sit}, \Delta Y_{Lit}) = (1+\delta_{1S})\sigma_\eta^2 + (1+\delta_{2S})\sigma_{\Delta u}^2,$$

$$Cov(\Delta Y_{Sit}, \Delta Y_{Lit-1}) = (1+\delta_{2S}) Cov(\Delta u_{it}, \Delta u_{it-1}),$$

$$Cov(\Delta Y_{Sit}, \Delta Y_{Lit-2}) = (1+\delta_{2S}) Cov(\Delta u_{it}, \Delta u_{it-2}),$$

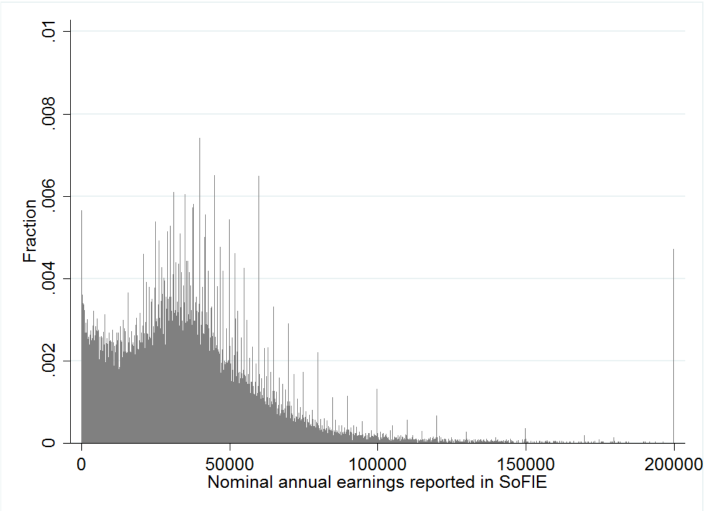
$$Cov(\Delta Y_{Sit}, \Delta Y_{Lit-k}) = 0, k > 2,$$

$$Cov(\Delta Y_{Sit-k}, \Delta Y_{Lit}) = Cov(\Delta Y_{Sit}, \Delta Y_{Lit-k}),$$

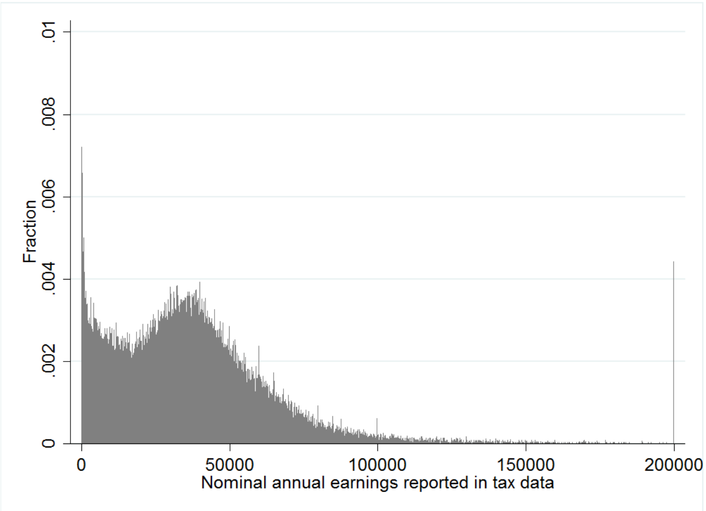
where $\sigma_{\Delta u}^2 = Var(\Delta u_{it}) = (1+(1-\theta)^2+\theta^2)\sigma_\omega^2$, $Cov(\Delta u_{it}, \Delta u_{it-1}) = ((\theta-1)+\theta(1-\theta))\sigma_\omega^2$, and $Cov(\Delta u_{it}, \Delta u_{it-2}) = -\theta\sigma_\omega^2$.

The vector of parameters of interest in this model is $(\sigma_\eta^2, \sigma_\omega^2, \theta, \delta_{1S}, \delta_{2S}, \sigma_{S\nu}^2, \sigma_{L\nu}^2)$ are identified by comparing the theoretical moments in the above equations with the empirical second moments (variances and covariances) of the changes in SoFIE and LEED log(earnings). Minimum distance estimation chooses the vector of parameter estimates to minimise the weighted sum of squared differences between the vectors of empirical and model-predicted second moments. Optimal minimum distance (OMD) estimation involves using as the weight matrix the inverse of the sampling variance-covariance matrix of the empirical moments. However, this involves the fourth moments of the data which, as Altonji and Segal (1996) show, results is substantial finite sample estimation bias due to correlation between the second and fourth moments. For this reason, instead of the OMD, we use as weight matrix the diagonal matrix which has the inverse of the sampling variances on the diagonal. This weighting approach, which takes account of the different variability across the second moments being fit by the model but not the correlations between the moments, has also been used by Hyslop (2001) and Pischke (1995).

Figure 1: Distributions of positive earnings – Sample 2
(A) SoFIE earnings



(B) LEED earnings



(C) log(SoFIE earnings) - log(LEED earnings)

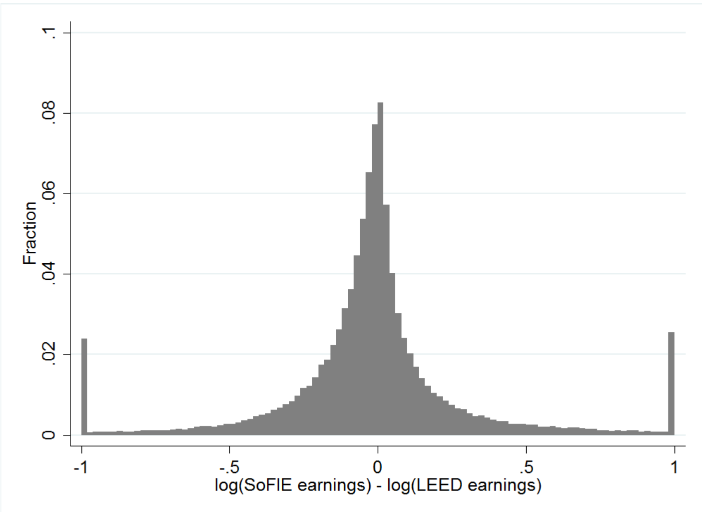
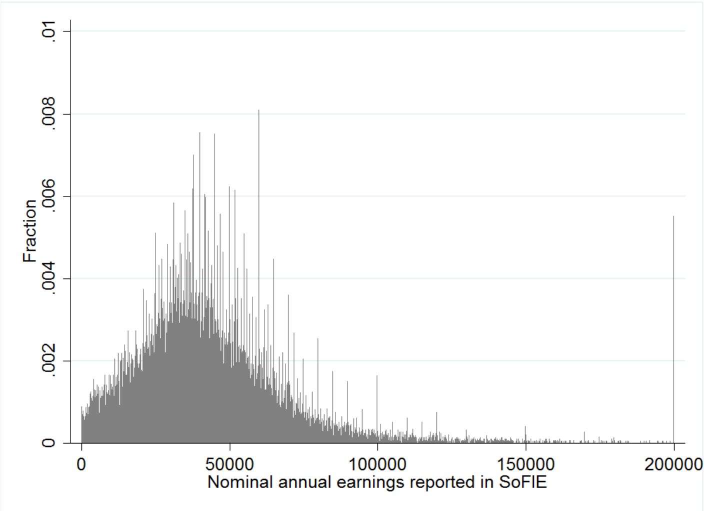
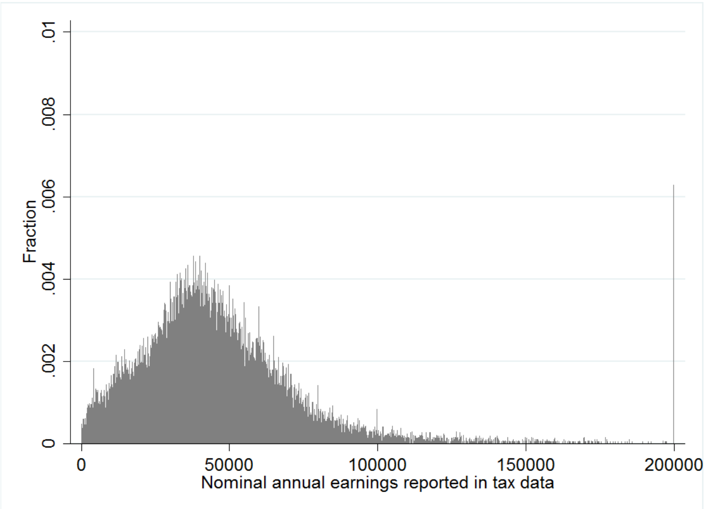


Figure 2: Distributions of positive earnings – Sample 4

(A) SoFIE earnings



(B) LEED earnings



(C) log(SoFIE earnings) - log(LEED earnings)

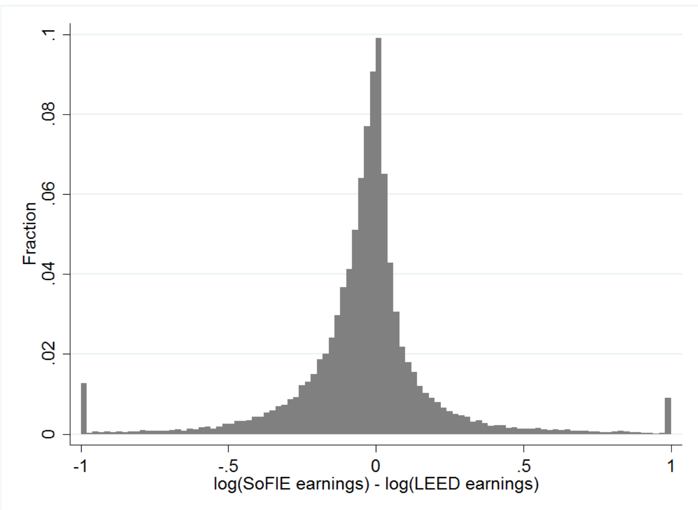


Table 1: Descriptive statistics – SoFIE and LEED matched samples

	Unmatched Sample	Unbalanced Panels (1)	(2)	Balanced Panels (3)	(4)
Age	41.81	41.77	40.84	43.04	43.32
	(13.51)	(12.46)	(12.63)	(10.4)	(10.11)
Female	0.59	0.53	0.57	0.59	0.52
	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)
European	0.57	0.76	0.74	0.77	0.81
	(0.50)	(0.43)	(0.44)	(0.42)	(0.39)
Maori	0.12	0.12	0.13	0.12	0.10
	(0.33)	(0.32)	(0.34)	(0.32)	(0.30)
Pacific Islander	0.12	0.05	0.05	0.05	0.04
	(0.32)	(0.21)	(0.23)	(0.22)	(0.20)
Asian	0.16	0.06	0.06	0.05	0.04
	(0.37)	(0.23)	(0.23)	(0.22)	(0.19)
High school	0.33	0.27	0.28	0.26	0.26
	(0.47)	(0.44)	(0.45)	(0.44)	(0.44)
Vocational	0.27	0.36	0.35	0.36	0.38
	(0.44)	(0.48)	(0.48)	(0.48)	(0.49)
Bachelor's degree	0.11	0.12	0.12	0.12	0.13
	(0.32)	(0.33)	(0.32)	(0.32)	(0.33)
Higher degree	0.06	0.07	0.06	0.07	0.08
	(0.23)	(0.25)	(0.24)	(0.25)	(0.27)
SoFIE: Employed	0.60	0.72	0.81	0.84	1
	(0.49)	(0.45)	(0.39)	(0.37)	
Self-employed	0.17	0.16	0	0	0
	(0.38)	(0.37)			
Hours worked/week	38.36	38.88	38.17	38.31	39.96
	(16.65)	(14.91)	(13.73)	(13.47)	(12.17)
Earnings ($)	20,579	27,798	31,525	35,010	45,974
	(31,268)	(34,578)	(35,106)	(37,502)	(32,752)
LEED: Employed	—	0.74	0.81	0.82	1
		(0.44)	(0.40)	(0.38)	
No. jobs	—	1.14	1.24	1.21	1.45
		(1.12)	(1.11)	(0.99)	(0.87)
No. months earnings	—	7.81	8.65	9.12	11.61
		(5.27)	(4.9)	(4.73)	(1.4)
Earnings ($)	—	28,081	30,992	34,882	47,644
		(32,812)	(32,806)	(34,486)	(33,679)
log(Sofie/LEED earn)		-0.02	-0.02	-0.04	-0.04
	—	(0.58)	(0.56)	(0.49)	(0.38)
abs[log(Sofie/LEED earn)]		0.26	0.25	0.21	0.17
	—	(0.52)	(0.5)	(0.45)	(0.35)
No. Individuals	1,383	24,138	22,017	7,104	4,572
No. Observations	3,417	116,643	97,962	56,832	36,576

Notes: Sample (1) is the full matched sample; (2) excludes self-employed observations; (3) is the balanced panel of persons; and (4) is the balanced panel with SoFIE and LEED earnings in each year. Standard deviations are in parentheses. All earnings are in nominal $-values. Sample sizes throughout the paper are randomly rounded to base 3 to maintain confidentiality.

Table 2: SoFIE and LEED Employment Margin Agreement

SoFIE earnings:	LEED earnings: None	Positive	Total
	(1): Full matched sample		
Non-positive	22.0	5.6	27.6
Positive	4.0	68.4	72.4
Total	26.0	74.0	100
No. observations			116,643
	(2): Excluding the self-employed		
Zero	15.1	3.8	18.9
Positive	4.3	76.8	81.1
Total	19.4	80.6	100
No. observations			97,962
	(3): Balanced panel of persons		
Zero	13.6	2.7	16.3
Positive	3.9	79.8	83.7
Total	17.5	82.5	100
No. observations			56,832

Notes: All entries are cell percentages of the total.

Table 3: SoFIE and LEED earnings comparisons

	(SoFIE Emp,LEED Emp)		
	(1,0)	(0,1)	(1,1)
(1) Full matched sample			
SoFIE log(earnings):			
mean	9.48	—	10.20
std dev.	1.89		1.06
LEED log(earnings):			
mean	—	8.51	10.22
std dev.		2.04	1.03
No. obs	4,719	6,579	79,734
(2) Excluding the self-employed			
SoFIE log(earnings):			
mean	9.58	—	10.22
std dev.	1.85		1.03
LEED log(earnings):			
mean	—	7.82	10.24
std dev.		1.94	1.01
No. obs	4,185	3,735	75,225
(3) Balanced panel of persons			
SoFIE log(earnings):			
mean	9.66	—	10.33
std dev.	1.81		0.98
LEED log(earnings):			
mean	—	7.64	10.36
std dev.		2.01	0.95
No. obs	2,208	1,533	45,336
(4) Balanced panel of SoFIE & LEED earnings			
SoFIE log(earnings):			
mean	—	—	10.51
std dev.			0.77
LEED log(earnings):			
mean	—	—	10.55
std dev.			0.74
No. obs			36,576

Notes: Estimates are based on the respective subsamples for which earnings exist.

Table 4: Differences between SoFIE and LEED log(earnings)

	Sample			
	(1)	(2)	(3)	(4)
Mean difference	-0.02	-0.02	-0.04	-0.04
Standard deviation	0.58	0.56	0.49	0.38
Fraction within				
0 log points	0.001	0.001	0.002	0.002
+/- 1 log points	0.087	0.088	0.097	0.106
+/- 5 log points	0.326	0.332	0.358	0.388
+/- 10 log points	0.503	0.512	0.545	0.584
+/- 20 log points	0.692	0.702	0.737	0.778
+/- 50 log points	0.876	0.883	0.907	0.938
+/- 100 log points	0.947	0.952	0.963	0.979
No. individuals	18,438	17,814	6,351	4,572
No. observations	79,734	75,225	45,336	36,576

Notes: For each sample, we use all person-year observations that have both SoFIE and LEED positive earnings reported.

Table 5: Correlates of differences between SoFIE and LEED earnings

Dependent variable:	log(earn) difference			abs(log(earn) difference)		
Sample:	(2)	(3)	(4)	(2)	(3)	(4)
Age 25-54	0.02	0.01	0.01	-0.01	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Age<25	0.02	0.01	0.02	0.00	-0.03	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	0.01	0.02	0.01	-0.01	-0.02	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Maori	-0.02	-0.01	-0.01	0.03	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Pacific Islander	-0.08	-0.08	-0.07	0.05	0.04	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	-0.06	-0.05	-0.05	0.02	0.03	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Other ethnicity	-0.07	-0.03	-0.03	0.02	-0.01	0.00
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
High school	0.01	0.02	0.02	-0.03	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Vocational	0.02	0.02	0.02	-0.04	-0.03	-0.03
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Bachelor degree	0.02	0.03	0.02	-0.06	-0.05	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Higher degree	0.02	0.03	0.03	-0.05	-0.04	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Weekly hours (x10)	0.04	0.03	0.02	-0.03	-0.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. LEED jobs	-0.02	-0.02	-0.02	0.03	0.03	0.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. LEED months	-0.09	-0.08	-0.07	-0.09	-0.09	-0.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.117	0.096	0.064	0.201	0.186	0.136
No. individuals	16,578	6,237	4,566	16,578	6,237	4,563
No. observations	67,905	41,949	34,968	67,905	41,949	34,968

Notes: Each column reports estimates from the regression of either the difference between log(SoFIE earnings) and log(LEED earnings), or the absolute value of this difference. The sample sizes differ from Table 4 because of missing covariates.

Table 6: Measurement error regressions

Covariate:	Sample (1)	(2)	(3)	(4)
(A) Dependent variable: Y_{Sit}= log(SoFIE earnings)				
Y_{Lit} (β)	0.873	0.873	0.893	0.911
	(.002)	(.002)	(.002)	(.003)
Intercept (α)	1.278	1.280	1.068	0.899
	(.020)	(.020)	(.025)	(.028)
R^2	0.718	0.726	0.758	0.763
(B) Dependent variable: Y_{Lit}= log(LEED earnings)				
Y_{Sit} (β)	0.823	0.832	0.848	0.837
	(.002)	(.002)	(.002)	(.002)
Intercept (α)	1.832	1.742	1.606	1.753
	(.019)	(.019)	(.023)	(.026)
R^2	0.718	0.726	0.758	0.763
(C) Dependent variable: DY_{it}= log(SoFIE earnings) - log(LEED earnings)				
Y_{Li} (β)	-0.101	-0.100	-0.074	-0.047
	(.005)	(.005)	(.007)	(.008)
$(Y_{Lit} - Y_{Li})$ (δ)	-0.220	-0.230	-0.213	-0.206
	(.009)	(.010)	(.013)	(.014)
Intercept (α)	1.016	1.008	0.736	0.455
	(.052)	(.054)	(.073)	(.085)
R^2	0.061	0.065	0.060	0.048
No. individuals	18,438	17,814	6,351	4,572
No. observations	79,734	75,225	45,336	36,576

Notes: Notes: Panels A reports results from the regression: $Y_{Sit} = \alpha + \beta Y_{Lit} + u_{Sit}$; and panel B reports results of the reverse regression. Panel C reports results of the regression:
$DY_{it} = \alpha + \beta Y_{Li} + \delta(Y_{Lit} - Y_{Li}) + \epsilon_{it}$
where DY_{it} is the difference between individual-i's SoFIE and LEED log(earnings) in year-t, Y_{Li} is their average log(LEED earnings) over the sample period, and $(Y_{Lit} - Y_{Li})$ is the annual deviation from this average.

Table 7: Employment margin transition matrices

	Working(t) in				
Working(t-1) in:	Neither	LEED Only	SoFIE Only	Both	Total
	(1) Full matched sample				
Neither (21.8)	85.4	4.8	2.2	7.5	100
LEED Only(5.5)	21.8	50.9	0.8	26.4	100
SoFIE Only(4.0)	10.9	1.4	73.0	14.6	100
Both (68.6)	2.6	1.7	0.9	94.8	100
Total (100)	22.1	5.1	4.1	68.7	100
	(2) Excluding self-employed				
Neither (14.7)	82.7	5.0	2.5	9.8	100
LEED Only(3.6)	25.6	35.6	1.1	37.6	100
SoFIE Only(4.2)	8.0	1.0	76.1	14.7	100
Both (77.6)	1.9	1.3	0.8	96.0	100
Total (100)	14.8	3.0	4.2	77.9	100
	(3) Balanced panel of persons				
Neither (13.4)	83.2	4.6	2.3	9.9	100
LEED Only(2.8)	27.4	36.4	0.6	35.3	100
SoFIE Only(3.9)	7.4	0.6	78.2	13.6	100
Both (79.9)	1.6	1.0	0.7	96.7	100
Total (100)	13.5	2.5	3.9	80.1	100

Notes: All table entries are percentages. Percentages sum to 100 in each row. Percentages in parentheses sum to 100 in each panel.

Table 8: The covariance structure of differences in SoFIE and LEED log(earnings)

A: Unbalanced panel of earnings

	log(SoFIE earn) - log(LEED earn) in Wave:							
Wave:	1	2	3	4	5	6	7	8
1	**0.255**	0.347	0.124	0.097	0.068	0.068	0.065	0.094
	(.024)							
2	0.077	**0.253**	0.248	0.098	0.116	0.084	0.090	0.105
	(.014)	(.025)						
3	0.025	0.050	**0.245**	0.269	0.165	0.114	0.130	0.092
	(.005)	(.006)	(.019)					
4	0.020	0.020	0.054	**0.247**	0.282	0.135	0.140	0.128
	(.007)	(.005)	(.008)	(.022)				
5	0.014	0.025	0.033	0.056	**0.250**	0.277	0.143	0.130
	(.005)	(.005)	(.006)	(.009)	(.025)			
6	0.014	0.017	0.022	0.026	0.052	**0.203**	0.289	0.164
	(.004)	(.004)	(.004)	(.004)	(.007)	(.018)		
7	0.014	0.018	0.024	0.026	0.026	0.048	**0.209**	0.280
	(.004)	(.004)	(.005)	(.005)	(.005)	(.007)	(.021)	
8	0.022	0.025	0.020	0.030	0.029	0.032	0.055	**0.285**
	(.006)	(.006)	(.005)	(.008)	(.008)	(.006)	(.008)	(.031)
Mean	-0.015	-0.037	-0.048	-0.041	-0.025	-0.036	-0.045	-0.044
	(.007)	(.007)	(.007)	(.007)	(.007)	(.006)	(.006)	(.007)

B: Balanced panel of earnings

	log(SoFIE earn) - log(LEED earn) in Wave:							
Wave:	1	2	3	4	5	6	7	8
1	**0.193**	0.352	0.121	0.095	0.070	0.084	0.079	0.095
	(.025)							
2	0.064	**0.168**	0.247	0.108	0.110	0.098	0.109	0.105
	(.016)	(.024)						
3	0.019	0.037	**0.131**	0.287	0.194	0.146	0.120	0.101
	(.004)	(.005)	(.014)					
4	0.015	0.016	0.037	**0.124**	0.295	0.188	0.146	0.109
	(.003)	(.004)	(.005)	(.017)				
5	0.010	0.015	0.023	0.035	**0.110**	0.272	0.177	0.128
	(.003)	(.003)	(.004)	(.005)	(.011)			
6	0.013	0.014	0.019	0.023	0.032	**0.125**	0.274	0.158
	(.003)	(.004)	(.003)	(.004)	(.004)	(.014)		
7	0.012	0.016	0.015	0.018	0.021	0.034	**0.122**	0.240
	(.003)	(.005)	(.003)	(.003)	(.003)	(.006)	(.020)	
8	0.019	0.019	0.016	0.017	0.019	0.025	0.037	**0.198**
	(.005)	(.006)	(.004)	(.004)	(.004)	(.005)	(.006)	(.030)
Mean	-0.026	-0.040	-0.050	-0.050	-0.040	-0.045	-0.046	-0.050
	(.007)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.007)

Notes: Variances in **bold** on the diagonal, covariances below the diagonal, and correlations above. Standard errors are in parentheses below the variances and covariances. Means and standard errors are in the final two rows.

Table 9: The covariance structure of SoFIE and LEED log(earnings) changes – Males

	ΔY_{Si2}	ΔY_{Si3}	ΔY_{Si4}	ΔY_{Si5}	ΔY_{Si6}	ΔY_{Si7}	ΔY_{Si8}	ΔY_{Li2}	ΔY_{Li3}	ΔY_{Li4}	ΔY_{Li5}	ΔY_{Li6}	ΔY_{Li7}	ΔY_{Li8}
ΔY_{Si2}	**0.224**	-0.337	-0.011	-0.005	-0.002	-0.024	-0.025	0.502	-0.034	0.058	-0.004	-0.029	-0.021	0.000
	(.033)													
ΔY_{Si3}	-0.077	**0.236**	-0.281	-0.113	-0.059	0.032	-0.022	-0.019	0.372	-0.094	-0.042	0.003	0.032	0.021
	(.026)	(.044)												
ΔY_{Si4}	-0.002	-0.050	**0.133**	-0.313	-0.061	-0.035	0.082	0.001	-0.066	0.367	0.022	-0.050	-0.024	0.032
	(.005)	(.015)	(.023)											
ΔY_{Si5}	-0.001	-0.019	-0.039	**0.117**	-0.298	-0.029	-0.024	-0.001	-0.018	-0.046	0.308	-0.009	0.006	-0.017
	(.004)	(.006)	(.015)	(.019)										
ΔY_{Si6}	0.000	-0.011	-0.008	-0.039	**0.145**	-0.321	-0.043	0.009	-0.002	-0.054	-0.069	0.388	0.067	-0.066
	(.005)	(.009)	(.004)	(.013)	(.025)									
ΔY_{Si7}	-0.004	0.006	-0.005	-0.004	-0.045	**0.136**	-0.274	0.012	-0.008	0.015	-0.033	0.001	0.427	-0.131
	(.007)	(.011)	(.005)	(.003)	(.018)	(.022)								
ΔY_{Si8}	-0.006	-0.005	0.014	-0.004	-0.007	-0.046	**0.211**	0.001	0.009	0.069	0.001	-0.040	-0.117	0.436
	(.010)	(.009)	(.008)	(.004)	(.004)	(.013)	(.030)							
ΔY_{Li2}	0.099	-0.004	0.000	0.000	0.001	0.002	0.000	**0.173**	-0.192	-0.047	0.016	-0.043	0.007	0.005
	(.015)	(.009)	(.004)	(.003)	(.003)	(.003)	(.004)	(.023)						
ΔY_{Li3}	-0.005	0.057	-0.008	-0.002	0.000	-0.001	0.001	-0.025	**0.099**	-0.276	0.004	0.025	-0.008	0.021
	(.008)	(.013)	(.005)	(.002)	(.003)	(.002)	(.003)	(.016)	(.021)					
ΔY_{Li4}	0.008	-0.013	0.037	-0.004	-0.006	0.002	0.009	-0.005	-0.024	**0.078**	-0.263	-0.069	-0.012	-0.004
	(.006)	(.006)	(.006)	(.005)	(.003)	(.004)	(.007)	(.005)	(.007)	(.011)				
ΔY_{Li5}	-0.001	-0.005	0.002	0.028	-0.007	-0.003	0.000	0.002	0.000	-0.019	**0.069**	-0.343	-0.061	0.003
	(.003)	(.004)	(.004)	(.006)	(.005)	(.003)	(.004)	(.003)	(.003)	(.007)	(.010)			
ΔY_{Li6}	-0.004	0.000	-0.006	-0.001	0.046	0.000	-0.006	-0.006	0.002	-0.006	-0.028	**0.097**	-0.199	-0.034
	(.005)	(.007)	(.004)	(.006)	(.010)	(.004)	(.005)	(.003)	(.003)	(.004)	(.008)	(.015)		
ΔY_{Li7}	-0.003	0.005	-0.003	0.001	0.008	0.048	-0.016	0.001	-0.001	-0.001	-0.005	-0.019	**0.093**	-0.267
	(.004)	(.007)	(.004)	(.003)	(.007)	(.010)	(.009)	(.003)	(.002)	(.003)	(.003)	(.009)	(.017)	
ΔY_{Li8}	0.000	0.004	0.004	-0.002	-0.009	-0.018	0.075	0.001	0.002	0.000	0.000	-0.004	-0.030	**0.139**
	(.004)	(.004)	(.004)	(.003)	(.004)	(.009)	(.012)	(.003)	(.003)	(.004)	(.003)	(.003)	(.011)	(.021)
Mean	0.086	0.086	0.054	0.053	0.051	0.041	-0.017	0.120	0.082	0.058	0.053	0.053	0.034	-0.011
	(.010)	(.010)	(.008)	(.007)	(.008)	(.008)	(.010)	(.009)	(.007)	(.006)	(.006)	(.007)	(.007)	(.008)

Notes: The estimates are based on the balanced 8-year employed panel of 2,181 males. Variances on the diagonal **bold**, covariances below the diagonal, and correlations above. Standard errors are in parentheses below the variances and covariances. Means and standard errors are in the final two rows.

Table 10: Summary of SoFIE and LEED log(earnings) changes

lag	Average variance or correlation			
k	$(\Delta Y_{Sit},\Delta Y_{Sit-k})$	$(\Delta Y_{Lit},\Delta Y_{Lit-k})$	$(\Delta Y_{Sit-k},\Delta Y_{Lit})$	$(\Delta Y_{Sit},\Delta Y_{Lit-k})$
		(A) Males		
Variance	0.172	0.107	—	—
0	1	1	0.400	0.400
1	-0.304	-0.257	-0.030	-0.053
2	-0.051	-0.042	-0.019	-0.029
3	-0.031	0.008	-0.011	0.003
4	0.038	-0.018	0.011	0.023
5	-0.023	0.014	0.000	0.010
6	-0.025	0.005	0.000	0.001
		(B) Females		
Variance	0.321	0.205	—	—
0	1	1	0.572	0.572
1	-0.270	-0.206	-0.035	-0.100
2	-0.090	-0.100	-0.091	-0.051
3	-0.014	-0.014	-0.018	-0.016
4	-0.007	-0.009	-0.009	0.018
5	0.007	-0.006	0.002	-0.013
6	-0.033	-0.020	-0.024	-0.030

Notes: Panel (A) summarises the average variances and correlations of male earnings changes in Table 9; panel (B) summarises the verage variances and correlations of female earnings changes in Table A1

Table 11: Estimated models of earnings dynamics and measurement errors

	Males				Females			
Parameter	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
σ^2_η	0.027	0.034	0.033	0.035	0.094	0.086	0.086	0.084
	(.006)	(.008)	(.008)	(.009)	(.012)	(.011)	(.011)	(.012)
σ^2_ω	0.035	0.005	0.006	0.005	0.061	0.035	0.035	0.036
	(.003)	(.002)	(.002)	(.002)	(.007)	(.005)	(.005)	(.005)
θ	0.144	0.407	0.401	0.404	0.368	0.461	0.460	0.456
	(.027)	(.062)	(.060)	(.063)	(.024)	(.034)	(.034)	(.034)
δ_{1S}	0.282	-0.087	-0.097	-0.122	-0.161	-0.023	-0.026	-0.017
	(.237)	(.221)	(.221)	(.237)	(.125)	(.132)	(.136)	(.144)
δ_{2S}	-0.830	0.692	0.670	0.690	-0.230	0.183	0.182	0.179
	(.041)	(.436)	(.429)	(.433)	(.116)	(.184)	(.184)	(.183)
$\sigma^2_{S\nu}$	0.050	0.046	0.042	—	0.085	0.074	0.075	—
	(.007)	(.007)	(.007)		(.009)	(.009)	(.010)	
$\sigma^2_{L\nu}$	—	0.023	0.021	—	—	0.025	0.022	—
		(.003)	(.003)			(.005)	(.005)	
$\sigma^2_{S\nu 0}$	—	—	0.102	—	—	—	0.070	—
			(.021)				(.017)	
$\sigma^2_{L\nu 0}$	—	—	0.058	—	—	—	0.065	—
			(.011)				(.013)	
GOF1	1,103.7	838.3	814.9	422.8	3,207.8	2,700.5	2,337.2	647.4
(df)	(99)	(98)	(96)	(84)	(99)	(98)	(96)	(84)
GOF2	942.2	831.8	789.4	356.7	1,782.9	1,379.0	1,189.8	366.7
(df)	(59)	(58)	(56)	(44)	(59)	(58)	(56)	(44)

Notes: Standard errors are in parentheses. The models are fit to the 105 distinct second moments of ΔY_{Sit} and ΔY_{Lit}. Model (1) assumes LEED earnings are measured without error, and has 6 parameters; model (2) allows classical measurement error in LEED earnings, and has 7 parameters; model (3) has 9 parameters, including separate classical measurement error variances in SoFIE and LEED earnings for the end-years; and model (4) has 21 parameters, including year-specific classical measurement error variances in SoFIE and LEED earnings. The GOF1-statistics are based on all 105 moments; while GOF2-statistics are based on just the 65 predicted non-zero moments (the contemporaneous, 1^{st} and 2^{nd} order moments).

Table 12: Predicted covariance structure of SoFIE and LEED log(earnings) changes – Males

	ΔY_{Si2}	ΔY_{Si3}	ΔY_{Si4}	ΔY_{Si5}	ΔY_{Si6}	ΔY_{Si7}	ΔY_{Si8}	ΔY_{Li2}	ΔY_{Li3}	ΔY_{Li4}	ΔY_{Li5}	ΔY_{Li6}	ΔY_{Li7}	ΔY_{Li8}
Predicted Variance-covariance matrix														
ΔY_{Si2}	**0.198**	-0.533	-0.040	0.000	0.000	0.000	0.000	0.288	-0.025	-0.029	0.000	0.000	0.000	0.000
ΔY_{Si3}	-0.093	**0.155**	-0.464	-0.046	0.000	0.000	0.000	-0.024	0.379	-0.029	-0.034	0.000	0.000	0.000
ΔY_{Si4}	-0.006	-0.065	**0.128**	-0.404	-0.048	0.000	0.000	-0.030	-0.031	0.439	-0.033	-0.035	0.000	0.000
ΔY_{Si5}	0.000	-0.006	-0.051	**0.123**	-0.294	-0.049	0.000	0.000	-0.036	-0.033	0.459	-0.031	-0.035	0.000
ΔY_{Si6}	0.000	0.000	-0.006	-0.038	**0.134**	-0.337	-0.037	0.000	0.000	-0.036	-0.032	0.407	-0.029	-0.027
ΔY_{Si7}	0.000	0.000	0.000	-0.006	-0.046	**0.136**	-0.292	0.000	0.000	0.000	-0.036	-0.030	0.397	-0.024
ΔY_{Si8}	0.000	0.000	0.000	0.000	-0.006	-0.049	**0.211**	0.000	0.000	0.000	0.000	-0.027	-0.023	0.260
ΔY_{Li2}	0.045	-0.003	-0.004	0.000	0.000	0.000	0.000	**0.120**	-0.489	-0.022	0.000	0.000	0.000	0.000
ΔY_{Li3}	-0.003	0.045	-0.003	-0.004	0.000	0.000	0.000	-0.051	**0.089**	-0.360	-0.027	0.000	0.000	0.000
ΔY_{Li4}	-0.004	-0.003	0.045	-0.003	-0.004	0.000	0.000	-0.002	-0.030	**0.081**	-0.244	-0.026	0.000	0.000
ΔY_{Li5}	0.000	-0.004	-0.003	0.045	-0.003	-0.004	0.000	0.000	-0.002	-0.019	**0.077**	-0.268	-0.026	0.000
ΔY_{Li6}	0.000	0.000	-0.004	-0.003	0.045	-0.003	-0.004	0.000	0.000	-0.002	-0.022	**0.089**	-0.168	-0.020
ΔY_{Li7}	0.000	0.000	0.000	-0.004	-0.003	0.045	-0.003	0.000	0.000	0.000	-0.002	-0.015	**0.093**	-0.303
ΔY_{Li8}	0.000	0.000	0.000	0.000	-0.004	-0.003	0.045	0.000	0.000	0.000	0.000	-0.002	-0.034	**0.139**
Errors: Actual - Predicted														
ΔY_{Si2}	**0.025**	0.196	0.028	-0.005	-0.002	-0.024	-0.025	0.213	-0.010	0.088	-0.004	-0.029	-0.021	0.000
ΔY_{Si3}	0.016	**0.081**	0.183	-0.067	-0.059	0.032	-0.022	0.005	-0.008	-0.065	-0.008	0.003	0.032	0.021
ΔY_{Si4}	0.004	0.016	**0.005**	0.091	-0.013	-0.035	0.082	0.031	-0.035	-0.072	0.055	-0.015	-0.024	0.032
ΔY_{Si5}	-0.001	-0.012	0.012	**-0.006**	-0.004	0.020	-0.024	-0.001	0.018	-0.013	-0.151	0.022	0.041	-0.017
ΔY_{Si6}	0.000	-0.011	-0.002	-0.001	**0.011**	0.016	-0.005	0.009	-0.002	-0.018	-0.037	-0.019	0.096	-0.039
ΔY_{Si7}	-0.004	0.006	-0.005	0.003	0.001	**0.000**	0.018	0.012	-0.008	0.015	0.003	0.031	0.030	-0.107
ΔY_{Si8}	-0.006	-0.005	0.014	-0.004	-0.001	0.003	**0.000**	0.001	0.009	0.069	0.001	-0.012	-0.094	0.176
ΔY_{Li2}	0.054	-0.001	0.004	0.000	0.001	0.002	0.000	**0.053**	0.297	-0.025	0.016	-0.043	0.007	0.005
ΔY_{Li3}	-0.002	0.012	-0.004	0.002	0.000	-0.001	0.001	0.025	**0.010**	0.084	0.030	0.025	-0.008	0.021
ΔY_{Li4}	0.011	-0.009	-0.007	-0.001	-0.002	0.002	0.009	-0.003	0.006	**-0.003**	-0.018	-0.043	-0.012	-0.004
ΔY_{Li5}	-0.001	-0.002	0.005	-0.017	-0.004	0.000	0.000	0.002	0.003	0.000	**-0.008**	-0.075	-0.035	0.003
ΔY_{Li6}	-0.004	0.000	-0.002	0.002	0.001	0.003	-0.002	-0.006	0.002	-0.004	-0.006	**0.008**	-0.031	-0.014
ΔY_{Li7}	-0.003	0.005	-0.003	0.004	0.011	0.003	-0.013	0.001	-0.001	-0.001	-0.003	-0.004	**0.000**	0.037
ΔY_{Li8}	0.000	0.004	0.004	-0.002	-0.006	-0.015	0.030	0.001	0.002	0.000	0.000	-0.002	0.004	**0.000**

Notes: Predictions based on model (4) presented in Table 11 for the sample of males.

Table 13: Predictions for earnings inequality

Variance:	Males SoFIE	Males LEED	Females SoFIE	Females LEED
True log(earnings) changes:				
σ^2_η	0.034		0.086	
Var(Δu_{it})	0.008		0.053	
Total	0.042		0.139	
Observed log(earnings) changes:				
$(1+\delta_{1S})^2.\sigma^2_{S\eta}$	0.028		0.082	
$(1+\delta_{2S})^2.Var(\Delta u_{it)}$	0.023		0.074	
$2.\sigma^2_{.\nu}$	0.093	0.047	0.148	0.050
Total	0.144	0.089	0.304	0.189
Observed log(earnings):				
Avg var(log(earnings))	0.164	0.135	0.424	0.352
Max $\sigma^2_{\lambda.i}$	0.012	0.012	0.017	0.017
Max var(meas. error)	0.065	0.035	0.104	0.042
Min var(true log(earnings))	0.100	0.099	0.320	0.310
Var(u_{it})	0.006		0.043	
Fraction of true var	0.063	0.063	0.133	0.137

Notes: Predictions based on model (2) in Table 11.

Table A1: The covariance structure of SoFIE and LEED log(earnings) changes – Females

	ΔY_{Si2}	ΔY_{Si3}	ΔY_{Si4}	ΔY_{Si5}	ΔY_{Si6}	ΔY_{Si7}	ΔY_{Si8}	ΔY_{Li2}	ΔY_{Li3}	ΔY_{Li4}	ΔY_{Li5}	ΔY_{Li6}	ΔY_{Li7}	ΔY_{Li8}
ΔY_{Si2}	**0.416**	-0.153	-0.075	0.008	0.005	0.015	-0.033	0.642	-0.006	-0.057	0.009	0.001	0.008	-0.024
	(.041)													
ΔY_{Si3}	-0.055	**0.314**	-0.331	-0.084	-0.024	-0.030	-0.001	-0.077	0.572	-0.109	-0.070	-0.030	-0.023	-0.004
	(.019)	(.027)												
ΔY_{Si4}	-0.027	-0.103	**0.310**	-0.320	-0.123	-0.033	0.005	-0.034	-0.139	0.565	-0.057	-0.130	-0.022	-0.006
	(.014)	(.022)	(.037)											
ΔY_{Si5}	0.003	-0.025	-0.095	**0.286**	-0.286	-0.062	-0.008	0.014	-0.054	-0.083	0.592	-0.053	-0.123	-0.030
	(.013)	(.013)	(.030)	(.037)										
ΔY_{Si6}	0.002	-0.007	-0.036	-0.079	**0.269**	-0.280	-0.106	0.028	-0.028	-0.065	-0.180	0.583	-0.030	-0.073
	(.008)	(.009)	(.009)	(.021)	(.040)									
ΔY_{Si7}	0.005	-0.009	-0.010	-0.018	-0.077	**0.281**	-0.250	-0.018	0.019	-0.056	-0.053	-0.111	0.516	0.046
	(.006)	(.007)	(.008)	(.007)	(.030)	(.042)								
ΔY_{Si8}	-0.013	0.000	0.002	-0.002	-0.034	-0.081	**0.375**	-0.030	-0.007	0.007	0.008	-0.051	-0.008	0.532
	(.008)	(.006)	(.008)	(.008)	(.011)	(.030)	(.068)							
ΔY_{Li2}	0.232	-0.024	-0.011	0.004	0.008	-0.005	-0.010	**0.314**	-0.203	-0.072	0.039	0.012	-0.008	-0.020
	(.022)	(.014)	(.013)	(.012)	(.014)	(.011)	(.007)	(.030)						
ΔY_{Li3}	-0.002	0.147	-0.035	-0.013	-0.007	0.005	-0.002	-0.052	**0.211**	-0.253	-0.095	-0.033	-0.013	-0.003
	(.014)	(.017)	(.014)	(.011)	(.006)	(.006)	(.007)	(.018)	(.022)					
ΔY_{Li4}	-0.016	-0.026	0.136	-0.019	-0.015	-0.013	0.002	-0.017	-0.050	**0.187**	-0.180	-0.105	-0.043	-0.027
	(.008)	(.011)	(.015)	(.009)	(.009)	(.009)	(.008)	(.010)	(.013)	(.016)				
ΔY_{Li5}	0.002	-0.017	-0.014	0.134	-0.040	-0.012	0.002	0.009	-0.018	-0.033	**0.180**	-0.262	-0.155	-0.018
	(.006)	(.007)	(.010)	(.017)	(.013)	(.007)	(.005)	(.006)	(.006)	(.009)	(.017)			
ΔY_{Li6}	0.000	-0.007	-0.030	-0.012	0.127	-0.025	-0.013	0.003	-0.006	-0.019	-0.047	**0.177**	-0.248	-0.074
	(.007)	(.007)	(.009)	(.012)	(.020)	(.015)	(.005)	(.010)	(.006)	(.006)	(.013)	(.018)		
ΔY_{Li7}	0.002	-0.005	-0.005	-0.026	-0.006	0.109	-0.002	-0.002	-0.002	-0.008	-0.026	-0.042	**0.159**	-0.087
	(.006)	(.005)	(.005)	(.007)	(.014)	(.016)	(.008)	(.006)	(.005)	(.005)	(.008)	(.013)	(.017)	
ΔY_{Li8}	-0.007	-0.001	-0.002	-0.007	-0.017	0.011	0.148	-0.005	-0.001	-0.005	-0.003	-0.014	-0.016	**0.206**
	(.006)	(.005)	(.005)	(.006)	(.012)	(.011)	(.020)	(.010)	(.004)	(.006)	(.005)	(.008)	(.008)	(.027)
Mean	0.129	0.058	0.084	0.083	0.071	0.051	0.002	0.127	0.081	0.080	0.063	0.078	0.059	0.004
	(.013)	(.011)	(.011)	(.011)	(.011)	(.011)	(.013)	(.011)	(.009)	(.009)	(.009)	(.009)	(.008)	(.009)

Notes: The estimates are based on the balanced 8-year employed panel of 2,394 females. Variances on the diagonal **bold**, covariances below the diagonal, and correlations above. Standard errors are in parentheses below the variances and covariances. Means and standard errors are in the final two rows.

Table A2: Estimated models of earnings dynamics and measurement errors

	Males			Females		
	SoFIE	LEED	Both	SoFIE	LEED	Both
	(1)	(2)	(3)	(1)	(2)	(3)
σ^2_η	0.047	0.026	0.030	0.104	0.077	0.084
	(.007)	(.005)	(.003)	(.013)	(.011)	(.007)
σ^2_ω	0.058	0.034	0.009	0.125	0.066	0.041
	(.007)	(.003)	(.002)	(.013)	(.006)	(.004)
θ	0.113	0.167	0.419	0.207	0.281	0.455
	(.029)	(.046)	(.063)	(.032)	(.043)	(.033)
$\sigma^2_{S\nu}$	—	—	0.049	—	—	0.078
			(.006)			(.009)
$\sigma^2_{L\nu}$	—	—	0.022	—	—	0.022
			(.002)			(.004)
GOF1	40.4	309.3	863.4	42.9	122.7	3,869.9
(df)	(25)	(25)	(100)	(25)	(25)	(100)
GOF2	46.5	265.4	902.9	28.4	123.2	1,843.2
(df)	(15)	(15)	(60)	(15)	(15)	(60)

Notes: Standard errors are in parentheses. The SoFIE or LEED data only models (columns (1) andd (2)) are fit to the 28 distinct second moments of ΔY_{Sit} or ΔY_{Lit} respectively. The combined SoFIE and LEED data models in column (3) are fit to the 105 distinct second moments of ΔY_{Sit} and ΔY_{Lit}. Model (3) allows classical measurement errors in SoFIE and LEED earnings. The GOF1-statistics are based on all moments; while GOF2-statistics are based on just the predicted non-zero moments (the contemporaneous, 1^{st} and 2^{nd} order moments).

Table A3: Predicted covariance structure of SoFIE and LEED log(earnings) changes – Females

	ΔY_{Si2}	ΔY_{Si3}	ΔY_{Si4}	ΔY_{Si5}	ΔY_{Si6}	ΔY_{Si7}	ΔY_{Si8}	ΔY_{Li2}	ΔY_{Li3}	ΔY_{Li4}	ΔY_{Li5}	ΔY_{Li6}	ΔY_{Li7}	ΔY_{Li8}
Predicted Variance-covariance matrix														
ΔY_{Si2}	**0.320**	-0.228	-0.073	0.000	0.000	0.000	0.000	0.513	-0.048	-0.078	0.000	0.000	0.000	0.000
ΔY_{Si3}	-0.074	**0.330**	-0.381	-0.074	0.000	0.000	0.000	-0.043	0.551	-0.050	-0.076	0.000	0.000	0.000
ΔY_{Si4}	-0.023	-0.119	**0.295**	-0.293	-0.079	0.000	0.000	-0.070	-0.050	0.618	-0.052	-0.085	0.000	0.000
ΔY_{Si5}	0.000	-0.023	-0.085	**0.284**	-0.300	-0.080	0.000	0.000	-0.078	-0.054	0.623	-0.056	-0.090	0.000
ΔY_{Si6}	0.000	0.000	-0.023	-0.084	**0.276**	-0.264	-0.070	0.000	0.000	-0.084	-0.054	0.671	-0.059	-0.080
ΔY_{Si7}	0.000	0.000	0.000	-0.023	-0.074	**0.281**	-0.236	0.000	0.000	0.000	-0.082	-0.057	0.688	-0.051
ΔY_{Si8}	0.000	0.000	0.000	0.000	-0.023	-0.077	**0.375**	0.000	0.000	0.000	0.000	-0.076	-0.051	0.524
ΔY_{Li2}	0.146	-0.012	-0.019	0.000	0.000	0.000	0.000	**0.253**	-0.319	-0.074	0.000	0.000	0.000	0.000
ΔY_{Li3}	-0.012	0.146	-0.012	-0.019	0.000	0.000	0.000	-0.074	**0.212**	-0.313	-0.080	0.000	0.000	0.000
ΔY_{Li4}	-0.019	-0.012	0.146	-0.012	-0.019	0.000	0.000	-0.016	-0.062	**0.188**	-0.172	-0.091	0.000	0.000
ΔY_{Li5}	0.000	-0.019	-0.012	0.146	-0.012	-0.019	0.000	0.000	-0.016	-0.033	**0.193**	-0.215	-0.093	0.000
ΔY_{Li6}	0.000	0.000	-0.019	-0.012	0.146	-0.012	-0.019	0.000	0.000	-0.016	-0.039	**0.171**	-0.225	-0.087
ΔY_{Li7}	0.000	0.000	0.000	-0.019	-0.012	0.146	-0.012	0.000	0.000	0.000	-0.016	-0.037	**0.159**	-0.093
ΔY_{Li8}	0.000	0.000	0.000	0.000	-0.019	-0.012	0.146	0.000	0.000	0.000	0.000	-0.016	-0.017	**0.206**
Errors: Actual - Predicted														
ΔY_{Si2}	**0.096**	0.076	-0.002	0.008	0.005	0.015	-0.033	0.129	0.041	0.021	0.009	0.001	0.008	-0.024
ΔY_{Si3}	0.019	**-0.017**	0.051	-0.011	-0.024	-0.030	-0.001	-0.034	0.021	-0.059	0.006	-0.030	-0.023	-0.004
ΔY_{Si4}	-0.004	0.016	**0.014**	-0.027	-0.044	-0.033	0.005	0.036	-0.089	-0.053	-0.005	-0.045	-0.022	-0.006
ΔY_{Si5}	0.003	-0.003	-0.010	**0.002**	0.014	0.017	-0.008	0.014	0.024	-0.030	-0.031	0.004	-0.033	-0.030
ΔY_{Si6}	0.002	-0.007	-0.013	0.005	**-0.008**	-0.016	-0.036	0.028	-0.028	0.019	-0.126	-0.088	0.029	0.007
ΔY_{Si7}	0.005	-0.009	-0.010	0.005	-0.003	**0.000**	-0.014	-0.018	0.019	-0.056	0.029	-0.055	-0.172	0.097
ΔY_{Si8}	-0.013	0.000	0.002	-0.002	-0.011	-0.005	**0.000**	-0.030	-0.007	0.007	0.008	0.025	0.043	0.008
ΔY_{Li2}	0.086	-0.012	0.008	0.004	0.008	-0.005	-0.010	**0.061**	0.116	0.002	0.039	0.012	-0.008	-0.020
ΔY_{Li3}	0.011	0.001	-0.023	0.006	-0.007	0.005	-0.002	0.021	**0.000**	0.059	-0.014	-0.033	-0.013	-0.003
ΔY_{Li4}	0.003	-0.014	-0.010	-0.007	0.005	-0.013	0.002	-0.001	0.012	**-0.001**	-0.008	-0.014	-0.043	-0.027
ΔY_{Li5}	0.002	0.003	-0.001	-0.012	-0.027	0.007	0.002	0.009	-0.002	0.000	**-0.013**	-0.047	-0.062	-0.018
ΔY_{Li6}	0.000	-0.007	-0.011	0.001	-0.019	-0.012	0.006	0.003	-0.006	-0.003	-0.008	**0.006**	-0.023	0.013
ΔY_{Li7}	0.002	-0.005	-0.005	-0.007	0.006	-0.036	0.011	-0.002	-0.002	-0.008	-0.010	-0.004	**0.000**	0.006
ΔY_{Li8}	-0.007	-0.001	-0.002	-0.007	0.002	0.023	0.002	-0.005	-0.001	-0.005	-0.003	0.002	0.001	**0.000**

Notes: Predictions based on model (4) presented in Table 11 for the sample of females.

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