

HIP, RIP, and the robustness of empirical earnings processes

FLORIAN HOFFMANN

Vancouver School of Economics, University of British Columbia

The dispersion of individual returns to experience, often referred to as heterogeneity of income profiles (HIP), is a key parameter in empirical human capital models, in studies of life-cycle income inequality, and in heterogeneous agent models of life-cycle labor market dynamics. It is commonly estimated from age variation in the covariance structure of earnings. In this study, I show that this approach is invalid and tends to deliver estimates of HIP that are biased upward. The reason is that any age variation in covariance structures can be rationalized by age-dependent heteroscedasticity in the distribution of earnings shocks. Once one models such age effects flexibly the remaining identifying variation for HIP is the shape of the tails of lag profiles. Credible estimation of HIP thus imposes strong demands on the data since one requires many earnings observations per individual and a low rate of sample attrition. To investigate empirically whether the bias in estimates of HIP from omitting age effects is quantitatively important, I thus rely on administrative data from Germany on quarterly earnings that follow workers from labor market entry until 27 years into their career. To strengthen external validity, I focus my analysis on an education group that displays a covariance structure with qualitatively similar properties like its North American counterpart. I find that a HIP model with age effects in transitory, persistent and permanent shocks fits the covariance structure almost perfectly and delivers small and insignificant estimates for the HIP component. In sharp contrast, once I estimate a standard HIP model without age-effects the estimated slope heterogeneity increases by a factor of thirteen and becomes highly significant, with a dramatic deterioration of model fit. I reach the same conclusions from estimating the two models on a different covariance structure and from conducting a Monte Carlo analysis, suggesting that my quantitative results are not an artifact of one particular sample.

KEYWORDS. Income processes, heterogeneity, human capital returns, identification, robustness.

JEL CLASSIFICATION. C23, D31, E24, J24, J31.

Florian Hoffmann: florian.hoffmann@ubc.ca

This study uses the weakly anonymous IAB Employment Sample. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and remote data access. I thank two anonymous referees for comments and suggestions that have significantly improved the paper. I am deeply indebted to Philip Oreopoulos, Shouyong Shi, and Victor Aguirregabiria for their guidance and support. I thank Michael Baker, Paul Beaudry, David Green, Gueorgui Kambourov, Thomas Lemieux, Jean-Marc Robin, Aloysius Siow, Kjetil Storesletten, and seminar participants at the CEPA seminar at the University of Toronto, the UBC empirical micro lunch seminar, and the 2012 conference on the use of administrative data at the IAB for helpful suggestions, and Benedikt Hartmann, Daniela Hochfellner, Peter Jacobebbinghaus, and other staff members at the FDZ-IAB for their hospitality. Daniel Shack has provided excellent research assistance. The usual disclaimer applies.

1. INTRODUCTION

How much do returns to labor market experience differ between individuals? An answer to this question is not only important for evaluating models of human capital accumulation as an empirical tool for studying life-cycle labor market dynamics, but also for quantifying the importance of individual heterogeneity for earnings and consumption inequality. Indeed, heterogeneity in earnings growth rates, often referred to as profile or slope heterogeneity, can generate sizeable and permanent increases of earnings inequality over the life cycle.¹ It also has important qualitative and quantitative predictions for individual-level consumption behavior and thereby on the welfare effects of income inequality.² For these reasons, quantifying profile heterogeneity convincingly and transparently is of central interest to a wide range of economic research.³

The dominating methodological framework for estimating heterogeneous returns to experience is a [Mincer \(1974\)](#) earnings equation with random coefficients and a dynamic error structure, often referred to as a HIP process.⁴ While the modeling details differ substantially across studies, two broad identification results for this class of models are well established. First, parameter identification requires panel data; and second, under the assumption that the model is well specified, profile heterogeneity and most other structural parameters can be point identified and estimated from the covariance structure of earnings. What remains unclear however is which particular features of covariance structures can and should be used for identification of slope heterogeneity and other model parameters and how sensitive parameter estimates are to model misspecification. It is thus popular to view the procedure of matching earnings processes to covariance structures as a “black box.”⁵ Whether existing estimation approaches deliver credible estimates of heterogeneity in the returns to experience is therefore unknown. Only recently has a small literature developed that attempts to resolve this issue. For example, [Guvenen \(2009\)](#) showed that profile heterogeneity generates a nonlinear relationship between labor market experience and residual income inequality that fits empirical age-profiles of residual variances well. It has therefore become common to use

¹See, for example, [Haider \(2001\)](#) and [Haider and Solon \(2006\)](#). I use “heterogeneous returns to labor market experience,” “profile heterogeneity,” “slope heterogeneity,” and “heterogeneous growth rates” interchangeably.

²See, for example, [Guvenen \(2007\)](#), [Primerici and van Rens \(2009\)](#) and [Guvenen and Smith \(2014\)](#). Summary papers of the heterogeneous-agents literature by [Guvenen \(2011\)](#) and of the consumption literature by [Meghir and Pistaferri \(2011\)](#) highlight the importance of earnings processes in structural modeling of life-cycle choices.

³Recent examples of quantitative life-cycle models with heterogeneous agents in which estimates from earnings processes are key inputs are [Storesletten, Telmer, and Yaron \(2004a\)](#), [Heathcote, Storesletten, and Violante \(2014\)](#) and [Low, Meghir, and Pistaferri \(2010\)](#) for consumption, [Abbott, Gallipoli, Meghir, and Violante \(2018\)](#) for education, [Erosa, Kambourov, and Fuster \(2016\)](#) for labor supply, [Huggett and Kaplan \(2016\)](#) for human capital, and [Farhi and Werning \(2013\)](#) and [Fukushima \(2010\)](#) for public finance. [Alvarez and Jermann \(2000\)](#) and [Krueger and Perri \(2006\)](#) studied the types of insurance mechanisms that are supported in decentralized markets depending on the persistence of exogenous shocks.

⁴“HIP” stands for “Heterogeneous Income Profiles.” Models without random coefficients are called “RIP,” which stands for “Restricted Income Profiles.” These labels were introduced by [Guvenen \(2007, 2009\)](#).

⁵For example, a recent study of earnings dynamics in administrative data from the US by [Guvenen, Karahan, Ozkan, and Song \(2015\)](#) criticizes the approach of matching covariance structures as “too opaque and a bit mysterious.”

this feature of the data as a calibration target in work that structurally estimates human capital models.⁶

In this paper, I make two distinct contributions to the literature on quantifying profile heterogeneity and modeling earnings dynamics. First, for a large class of earnings processes I show that age profiles of variances and higher-order autocovariances of residual earnings do not contain valid information for identifying heterogeneous returns to human capital accumulation. The reason is that *any* shape of variance profiles can be rationalized by age effects in the variances of transitory shocks. Similarly, a combination of age-heteroscedastic persistent and permanent shocks can match a wide range of age profiles in higher-order autocovariances. As a consequence, models that do not feature age-dependent heteroscedasticity tend to deliver biased estimates of slope heterogeneity. This is not merely a statistical issue since age effects in second moments are generated by various economic theories. Examples are search models, where reallocation of workers to better firm-matches via search generates a decline in residual variances over the life cycle, or models featuring career progression, where promotions and demotions become more likely in the middle of a life cycle. In fact, even the most basic human-capital accumulation process with less than full depreciation of the human capital stock can generate age heteroscedasticity in residual earnings. Without theoretical guidance regarding the functional form of age effects, it is best to leave it unrestricted and to model it flexibly.

On the other hand, the shape of lag-profiles at high orders provides a credible source of identification for slope heterogeneity, even in the presence of age effects. It is here where HIP imposes strong and unique predictions on the covariance structure. Intuitively, slope heterogeneity does not generate significant earnings differences among inexperienced workers, but its effect becomes increasingly strong as individuals accumulate labor market experience. At the same time, earnings of the young already partially reflect differences in earnings growth and are thus predictive of earnings differences many years later. In combination, this implies that the HIP component imposes strong and testable restrictions on high-order autocovariances. It is hard to think of any other mechanism that can generate this pattern, which renders the shape of lag profiles at their tails a clean source of identifying variation for profile heterogeneity. Conversely, in the absence of rich dynamics in these tails it is unlikely that slope heterogeneity is important.

Remarkably, these results can be derived simply by checking a collinearity condition. This remains true even in the most general specification considered in this paper, which introduces time effects in addition to age effects. More specifically, since I consider earnings processes that can be estimated by matching covariance structures, identification can be explored by exploiting the well established but rarely used equivalence of equally weighted minimum distance estimation—the dominating methodological approach in the literature—with the nonlinear least squares estimator. Viewing estimation and parametric identification from this perspective has the advantage that one can rely on the well-understood econometric theory of parametric regression analysis. Concepts such

⁶Examples are Guvenen, Kuruscu, and Ozkan (2014) and Huggett, Ventura, and Yaron (2011).

as omitted variable bias and multicollinearity carry over directly, rendering identification transparent and intuitive. This goes a long way in opening the “black box” of estimating earnings processes.

As a second contribution, I explore whether the omitted variable bias in estimates of profile heterogeneity from excluding age effects in innovation variances is likely to be important in practice. Since credible identification of slope heterogeneity needs to come from the shape of the right tail of lag profiles, this requires data with long worker-level time series, large sample sizes, and low attrition rates. Open-source panel data sets, such as the Panel Study of Income Dynamics (PSID) or the National Longitudinal Survey of Youth (NLSY), do not satisfy these criteria and are thus not well suited for estimating HIP earnings processes that flexibly control for age effects. Instead, I rely on a large administrative panel data set from German social security records. Individuals in these data are followed from time of labor market entry up until 27 years into their careers, and the spell-based recording enables me to generate samples on the quarterly rather than the annual frequency.⁷ A further advantage of the data is that it provides information on educational attainment, in contrast to administrative data from North America. Several central findings from my empirical analysis rely crucially on this information, for two major reasons. On the one hand, the largest education group in the German labor market displays an autocovariance structure of labor market earnings that shares the main qualitative features with the North American counterpart. On the other hand, the covariance structures are quite different across education groups, which permits carrying out a thorough robustness exercise.

The central empirical result coming out of this exercise is that omitting age effects in innovation variances can lead to a severe upward bias in estimates of profile heterogeneity. Estimating the standard HIP model without age effects as it is commonly specified in the literature on the sample of the largest education group delivers a variance of earnings growth rates that is economically and statistically highly significant. In sharp contrast, when I estimate my preferred specification, which features age effects and fits the data exceptionally well with relatively few parameters, the estimated slope heterogeneity decreases by a factor of thirteen and becomes statistically indistinguishable from zero.⁸ Since one may be worried that my results are an artifact of the earnings structure in my sample, I repeat my analysis using data from an education group with a very different covariance structure. Again I find that a standard HIP specification yields significant slope heterogeneity while the inclusion of age effects drives estimates to zero.

⁷Administrative data on earnings are increasingly used in economics. The high frequency at which earnings are recorded in the German data is one of its distinct features. Studies on worker mobility across firms, occupations, and employment states have highlighted the problems associated with time aggregation for quite some time, and it has become standard in this literature to use data on the monthly frequency. In contrast, I am not aware of any study in the earnings literature that uses data on a higher than the annual frequency. This is an important omission because just as time aggregation will yield downward biased estimates of worker mobility rates, it will also miss possibly economically significant fluctuations in individual earnings.

⁸My benchmark specification also includes time effects. In total, it has 62 parameters that are matched to cohort-specific covariance structures with over 56,000 elements. The model fits all of its features, such as the evolution of variances over the life cycle and over time, almost perfectly.

I complement my empirical analysis with a Monte Carlo analysis that replicates, in the simulated data, the cohort and age structure of the German data. The two central questions I address with this analysis are (i) whether a HIP component, if present in the true data generating process, can be recovered precisely from a finitely sized sample if one models age effects in innovation variances flexibly and (ii) whether estimates of the HIP component are systematically biased upward if such age effects are omitted. Both questions are answered assertively in the positive. Hence, samples of similar sizes like the IABS data are sufficient for implementation of the approach to identification of HIP suggested in this paper.

2. RELATION TO LITERATURE

The question of how dispersed individual earnings growth rates are has been explored at least since [Mincer's \(1958\)](#) work on human capital investments. [Ben-Porath \(1967\)](#) formulates more explicitly a model of human capital investments in which differences in the accumulation rate between individuals can generate heterogeneous slopes of experience-earnings profiles. Seminal studies by [Lillard and Weiss \(1979\)](#) and [Hause \(1980\)](#) were among the first to quantify this type of heterogeneity using panel data on labor income. The econometric models formulated in these studies have the interpretation of a [Mincer \(1974\)](#) earnings regression with random slopes and an added dynamic structure for the error term. [MaCurdy \(1982\)](#) carried out model specification tests by estimating various specifications for the dynamics of the error term. He concludes that slope heterogeneity is not an important component of life-cycle earnings dynamics. Subsequent papers in the literature, such as [Abowd and Card \(1989\)](#) and [Meghir and Pistaferri \(2004\)](#), adopt this view. However, [Baker \(1997\)](#) showed that MaCurdy's test for slope heterogeneity has low power in small samples and documents evidence for slope heterogeneity and modest persistence of shocks, a result that has been corroborated by [Haider \(2001\)](#) and [Guvenen \(2009\)](#).

As of now, the debate about the importance of HIP does not seem to be settled, possibly because there is little work on credible identification of profile heterogeneity and because of the data limitations discussed in the Introduction. Some progress toward understanding the sources of identifying variation for the main parameters of interests in earnings processes has been made recently, however. [Guvenen \(2009\)](#) showed that slope heterogeneity in a standard HIP model without age effects is identified from both the convexity of age profiles and the behavior of lag-profiles of earnings covariances. In line with his identification result, he also establishes that HIP models can replicate the age-profile of residual earnings inequality, which he documents to be convex, better than RIP models. However, as [Hryshko \(2012\)](#) showed, these results are not robust to a slight modification in the error process, hinting at the sensitivity of key parameters to model misspecification.⁹ Compared to these works, I consider a considerably larger family of earnings processes, and I explicitly explore the relationship between controlling for age effects flexibly on the one hand and the validity of estimates of the HIP component on

⁹This is directly implied by my identification results since a unit roots process generates linear age effects in age profiles of covariances.

the other hand. Furthermore, I explore identification by exploiting the equivalence between the common estimation method in the literature, referred to as equally weighted minimum distance estimation, and nonlinear least squares regression. This has at least two advantages. First, I can address the case with many more moments than parameters, which commonly applies to minimum-distance estimation. In contrast, identification is usually established in the literature by selecting K moments that uniquely solve for K parameters, that is, the exactly identified case. Second, conditions for identification in non-linear least squares are well understood and, as it turns out, can be checked quite easily for the family of models considered here. This facilitates the analysis of identification considerably, even though the earnings process considered here features three variance components distinguished by their persistence, all of which feature age-dependent heteroscedasticity and nonparametric time effects.

There is a large literature that emphasizes the importance of controlling flexibly for age and time effects when studying the sources of individual earnings variation over time and the life cycle, such as Storesletten, Telmer, and Yaron (2004b), Heathcote, Storesletten, and Violante (2005) and Lemieux (2006). Recent analyses of the covariance structure of earnings have also incorporated age effects in various components of the earnings process and find that they are important. Examples are Karahan and Ozkan (2013) and Lopez-Daneri (2016), who establish the presence of age effects in a RIP process estimated from the PSID, and Sanchez and Wellschmied (2017), who find substantial asymmetries and age effects in the distribution of earnings shocks in German administrative data. Baker and Solon (2003) and Blundell, Graeber, and Mogstad (2015) estimated, using administrative data from Canada and Norway, respectively, rich HIP processes that incorporate flexible specifications of age and time effects.¹⁰ The empirical model I estimate on the German administrative data is similar to theirs. The prime difference between these studies and mine is the focus. While they use earnings processes primarily to quantify the sources of individual life-cycle earnings variation and their changes over time, I study identification of profile heterogeneity and stress the omitted variable bias coming from omission of age effects in innovation variances. The result that age profiles of covariance structures cannot credibly identify slope heterogeneity, and that the bias from not modeling age effects flexibly can be severe is, to the best of my knowledge, new.

Two areas of research on life-cycle earnings dynamics have received particularly much attention recently.¹¹ The first exploits the joint dynamics of consumption and earnings for parameter identification. In most applications, such as in Hall and Mishkin (1982), Blundell, Pistaferri, and Preston (2009) or Heathcote, Storesletten, and Violante

¹⁰These studies build on an earlier literature that use earnings processes to quantify the sources of trends in earnings dynamics, innovated by Gottschalk and Moffitt (1994). Similar exercises, though with more restrictive models and less rich data, have been carried out for various countries, for example, by Moffitt and Gottschalk (2002) for the US, Biewen (2005) for Germany, and Dickens (2000) for the UK.

¹¹A recent study by Daly, Hryshko, and Manovskii (2017) that does not fall within these two areas finds that estimates of earnings processes are substantially affected by nonrandom missings in both, public-use panel data and high-quality administrative data. Nonrandom missing data can explain why estimates from earnings measured either in levels or in growth often differ substantially.

(2008), these dynamics merely provided overidentifying restrictions on the parameters of the earnings process. Indeed, [Arellano, Blundell, and Bonhomme \(2017\)](#) considered a model of consumption in which the transition density of the earnings process is non-parametrically identified from earnings data alone. They also propose an attractive two-step estimator in which this density is recovered in a first step. In some cases, however, consumption data may be necessary to achieve identification. For example, [Guvenen \(2007\)](#) and [Guvenen and Smith \(2014\)](#) considered models in which individuals learn about their abilities so that individual ability differences are not fully reflected in earnings, at least at an early stage of the life cycle. [Browning and Ejrnaes \(2014\)](#) and [Hryshko \(2014\)](#) specified earnings processes in which different variance components are correlated. Alan, [Browning and Ejrnaes \(2018\)](#) estimated a model in which heterogeneity in preference parameters and the parameters describing the earnings process are codependent. In these cases, identification relies explicitly on the comovement between consumption and earnings. At the same time, there are significant drawbacks from relying on consumption data. Examples are the lack of high-quality administrative panel data that simultaneously record earnings and consumption dynamics, the potential computational burden of estimating structural decision-theoretic models of consumption in the presence of an earnings process with many state variables, and the need to rely on strong parametric assumptions. As highlighted by [Meghir and Pistaferri \(2011\)](#), relying on large administrative data sets to estimate flexible earnings processes, the approach followed in this paper, should be seen as complementary. Furthermore, the central points of my paper that profile heterogeneity imposes strong restrictions on the tails of lag profiles of covariance structures and that omission of age effects leads to an upward bias in the estimates of the variance of these abilities are hard-wired into a HIP process and are thus independent of whether a process for consumption choices is specified or not. In practice, one important implication of my findings is that the restrictions on lag profiles imposed by a particular estimate of profile heterogeneity should be tested against the data if the estimation heavily relies on consumption data. For example, it is possible that the estimate of profile heterogeneity that best fits observed consumption behavior generates earnings dynamics that are at odds with the tail behavior of lag-profiles of earnings covariances. This provides a powerful overidentifying restriction.

The second area of active research departs from the conventional approach to earnings dynamics by going beyond autocovariance structures for estimation. For example, [Meghir and Pistaferri \(2004\)](#) allowed for ARCH-effects in the transitory and permanent innovations, and [Browning, Ejrnaes, and Alvarez \(2010\)](#) extended this framework to processes in which the majority of parameters are random variables. In both cases, identification needs to rely on more information than second moments. There has also been some progress on nonparametric identification of earnings transition densities, such as [Horowitz and Markatou \(1996\)](#), [Hirano \(2002\)](#), [Bonhomme and Robin \(2009\)](#), [Lochner and Shin \(2014\)](#), [Arellano, Blundell, and Bonhomme \(2017\)](#), and [Hu, Moffitt, and Sasaki \(2018\)](#). [De Nardi, Fella and Pardo \(2018\)](#) explored the implications of modeling earnings dynamics nonparametrically for consumption behavior. [Guvenen et al. \(2015\)](#) highlighted the need to move beyond second moments in a detailed study of earnings growth

in US administrative data. While these studies paint a richer picture of earnings dynamics than the process considered in my work, the focus is quite different. Indeed, if interest is in quantifying the importance of intercept and slope heterogeneity, some parametric restrictions need to be imposed on the earnings process. It is in this context in which I study identification. The focus on credible estimation of the HIP component is therefore one of the central features of my study that distinguishes it from these works.¹²

3. ECONOMETRIC FRAMEWORK, ESTIMATION, AND IDENTIFICATION

3.1 *The econometric model*

Let y_{ibt}^e be the log-earnings in period t of individual i born in year b who belongs to education group e . Assume that log earnings are described by the equation

$$y_{ibt}^e = \mu_{bt}^e + \widehat{y}_{ibt}^e, \quad (3.1)$$

where μ_{bt}^e represents a set of education specific cohort-time fixed effects and \widehat{y}_{ibt}^e is the error term. The focus of this study will be on the life-cycle dynamics of \widehat{y}_{ibt}^e . Given that this is a regression error term that needs to be assumed to be conditionally independent from the observed part of (3.1), controlling flexibly for age, cohort, and education effects is important. For example, if age effects in conditional first moments of log earnings are highly nonlinear, then improperly controlling for them will spuriously generate age effects in conditional second moments of the residual.¹³ The required flexibility is achieved by using the nonparametric specification in (3.1) for the observed part of the model rather than the more conventional Mincerian approach that estimates parametric linear regressions to obtain the residual of interest, \widehat{y}_{ibt}^e .

To describe the dynamics of \widehat{y}_{ibt}^e , some additional notation is required. To avoid clutter in indexing variables, I suppress the education superscript for the rest of the paper. Let $t_0(b)$ be the year a cohort b enters the labor market and define $\underline{t}_0 = \min\{t_0(b)\}$, which is the year the oldest cohort enters the data and hence the first sample period. Assume

¹²It is important to note that the model formulated below does not impose any restrictions on higher-order moments. The theoretical and empirical results established in my study are thus independent from the behavior of higher-order moments, such as skewness or excess kurtosis. If one is willing to impose additional distributional assumptions, the approach followed here could thus be combined with a second stage that identifies parameters governing higher-order moments. Suppose, for example, that one assumes that excess kurtosis in the distribution of earnings changes, as documented in Guvenen et al. (2015), is driven by the distribution of the returns to experience, β_i . If one postulates that β_i has a population distribution with, say, three parameters, written $f_\beta(\phi_1, \phi_2, \phi_3)$, then one requires at least three moment restrictions. Let $E_\beta^k(\phi_1, \phi_2, \phi_3)$ be the k th central moment of f_β . One restriction is the normalization, also used in my estimation, that $E_\beta^1(\phi_1, \phi_2, \phi_3) = 0$. Since the framework proposed below recovers the variance of β , written σ_β^2 , without explicit distributional assumptions, it can be used as a first-stage estimator for constructing a second moment condition $E_\beta^2(\phi_1, \phi_2, \phi_3) = \sigma_\beta^2$. A third restriction must come from higher-order moments. My study explores identification of σ_β^2 without any explicit distributional assumptions about $f_\beta(\phi_1, \phi_2, \phi_3)$. It is in this sense that the procedure of matching covariance structures is a semiparametric estimator.

¹³From now on, I will use “age” and “potential labor market experience” interchangeably since they correlate perfectly once one imposes a normalization on the age of labor market entry, as I do in the estimation.

that individuals of the same cohort and education group enter the labor market at the same time so that potential experience, interchangeably referred to as age, is given by $h_{bt} = t - t_0(b)$. The model of \widehat{y}_{ibt} is given by the following set of dynamic equations:

$$\widehat{y}_{ibt} = p_t * [\alpha_i + \beta_i * h_{bt} + u_{ibt}] + z_{ibt} + \varphi_t * \varepsilon_{ibt} \quad (3.2)$$

with

$$u_{ibt} = u_{ib,t-1} + v_{ibt} \quad (3.3)$$

$$z_{ibt} = \rho * z_{ib,t-1} + \lambda_t * \xi_{ibt}. \quad (3.4)$$

This model decomposes the life-cycle dynamics of residual log-earnings into three stochastic processes of different persistences. The first term ($\alpha_i + \beta_i * h_{bt} + u_{ibt}$) is a permanent component, updated each period by a permanent shock v_{ibt} ; the second term z_{ibt} is an AR(1)-process with persistence $\rho \in (0, 1)$; and the third term ε_{ibt} is a purely transitory component. The set of parameters $(p_t, \lambda_t, \varphi_t)_{t \geq t_0}$ are factor loadings, one for each component. They allow the process of \widehat{y}_{ibt} to change over time, so that different cohorts are subject to different life-cycle earnings dynamics.

Let x be some random variable, and assume that experience-dependent heteroscedasticity in its distribution can be described by a polynomial of degree J_x in h . All shocks and components of unobserved heterogeneity are assumed to have unconditional mean of zero and the following variance structure:

$$\text{var}(\alpha_i) = \widetilde{\sigma}_\alpha^2; \quad \text{var}(\beta_i) = \sigma_\beta^2; \quad \text{cov}(\alpha_i, \beta_i) = \sigma_{\alpha\beta}, \quad (3.5)$$

$$\text{var}(v_{ibt}) = \sum_{j=0}^{J_v} (h_{bt})^j * \delta_j; \quad \text{var}(u_{it_0(b)}) = \widetilde{\sigma}_{u_0}^2, \quad (3.6)$$

$$\text{var}(\xi_{ibt}) = \sum_{j=0}^{J_\xi} (h_{bt})^j * \gamma_j; \quad \text{var}(z_{it_0(b)}) = (\lambda_{t_0(b)})^2 * \sigma_{\xi_0}^2, \quad (3.7)$$

$$\text{var}(\varepsilon_{ibt}) = \sum_{j=0}^{J_\varepsilon} (h_{bt})^j * \phi_j. \quad (3.8)$$

This specification leaves initial conditions of the three experience-variance profiles unrestricted, which plays an important role in the empirical implementation below. No further distributional assumptions are required, but the factor loadings $(p_t, \lambda_t, \varphi_t)_{t \geq t_0}$ need to be normalized for some periods. The following restrictions are sufficient for identification:¹⁴

$$p_{t_0} = p_{(t_0+1)} = \lambda_{t_0} = \lambda_{(t_0+1)} = \varphi_{t_0} = 1. \quad (3.9)$$

This completes the description of the earnings process.

¹⁴See Section 3.4 and Appendix C in the Online Supplemental Material (Hoffmann (2019)).

3.2 Discussion

The process described by equations (3.2) to (3.8) is very flexible and nests the majority of specifications considered in the literature that feature heterogeneous returns to experience. A number of features are worth highlighting. First, the process is the sum of a permanent, a persistent, and a purely transitory component, a decomposition that has been suggested as early as [Friedman's \(1957\)](#) seminal study of individual consumption choices. All three components present labor market risks with different degrees of insurability and play a prominent role in structural models of consumption and savings decisions and in heterogeneous agents models. A precise interpretation of these shocks is difficult because they are modeled as unobserved components and because there is limited evidence on how they map into measurable characteristics and events. A number of recent studies have made significant progress on this issue, however. For example, [Polachek, Das, and Thamma-Apiroam \(2015\)](#) showed that permanent individual differences in earnings growth relate to differences in cognitive ability, personality traits, and family background. Various structural studies of life-cycle earnings and mobility dynamics, such as [Low, Meghir, and Pistaferri \(2010\)](#), [Hoffmann \(2010\)](#) and [Pavan \(2011\)](#), show that transitions across firms and between occupations generate substantial and persistent changes in residual earnings. [Postel-Vinay and Turon \(2010\)](#) document that a canonical job search model with job-to-job transitions can produce an earnings process with a persistence that is consistent with the data. [Altonji, Smith, and Vidangos \(2013\)](#) established a similar result and propose health shocks as another source of persistent earnings changes. [Guiso, Pistaferri, and Schivardi \(2005\)](#) and [Lamadon \(2016\)](#) found in matched employer-employee data that a sizeable part of persistent or permanent firm-level productivity shocks are passed on to workers, while transitory shocks are not. There is also growing evidence, summarized in a recent paper by [Davis and von Wachter \(2012\)](#), that job displacement is a source of highly persistent earnings loss. On the other hand, one-time bonus payments and a temporary absence from work are often cited as an example of transitory shocks, though there is less tangible evidence on this hypothesis. Another interpretation of purely transitory earnings variation is measurement error, consistent with the small estimates of its variance found in administrative data, as in [Baker and Solon \(2003\)](#) and as reported for the German data below. One may therefore conjecture that any economically meaningful shocks have at least some persistence.

A second important feature of the earnings process described above is the rich specification of age effects. It is the central result of this paper that a priori restrictions on age heteroscedasticity in the distribution of earnings shocks are a model misspecification that produces an upward bias in the estimate of profile heterogeneity. A flexible approach to modeling age heteroscedasticity is using polynomials, as in equations (3.6), (3.7), and (3.8).¹⁵ What is perhaps surprising at first is that point identification, holding fixed the degree of the polynomial, can be achieved even though multiple error components are allowed to be heteroscedastic in age. This result relies crucially on

¹⁵This may be viewed as a nonparametric series method to approximating the age structure of autocovariances. Notice however that it holds the degree of the polynomials fixed.

exploiting information in the entire covariance structure, not only its age variance profiles.

A third feature worth emphasizing is the presence of time effects in innovation variances. There is a large literature emphasizing the need to control flexibly for age and time effects when estimating empirical life-cycle models of conditional *first* moments of the earnings distribution, as reviewed above. The age and time structure of the model in (3.2) to (3.8) is an application of similar ideas to *second* moments of life-cycle earnings dynamics. Indeed, changes of innovation variances over the life cycle can be driven by either age or time effects. For consistent estimation of the former, it is thus crucial to control for the latter. As a consequence, the covariance structure needs to be disaggregated to the cohort level, which imposes large demands on the data.¹⁶ The specification chosen here allows for maximum flexibility. Each of the three variance components have their own factor loading. Since there are no distributional or functional form restrictions on these loadings, the specification of time effects is essentially nonparametric. Also notice that the factor loading λ_t enters the persistent component indirectly through its multiplication with the shock ξ_{ibt} , so that its impact on earnings dynamics fades gradually over time. A pattern of this form can be expected from the effects of business-cycle shocks or firm closures on earnings.¹⁷ Furthermore, initial conditions in the persistent component ($\lambda_{t_0(b)} * \sigma_{\xi_0}^2$) vary across cohorts indexed by b because different cohorts enter the labor market in different years.

The model could be enriched further, for example, by adding an MA(q) component or allowing for ARCH or GARCH in the distribution of shocks. I do not consider the former for two major reasons. First, introducing a MA(q) component would break point identification without changing the main result of the paper that omission of age effects causes an omitted variable bias of slope heterogeneity. Second, in empirical implementations I have found the MA(q) component to be insignificant.¹⁸ I do not allow for ARCH or GARCH because it would carry the process out of the family of processes that can be estimated from autocovariance structures. More importantly, the type of heteroscedasticity specified in equations (3.6), (3.7), and (3.8) can generate complex variance dynamics themselves, and it is neither clear that adding ARCH or GARCH would improve model validity nor that its parameters would be point identified.

¹⁶Alternatively, one can disaggregate the data to the age-time level, as in Abowd and Card (1989) and Blundell, Graeber, and Mogstad (2015).

¹⁷This specification is adopted from Baker and Solon (2003).

¹⁸The variance of transitory shocks is not point identified in the presence of measurement error. This result generalizes to MA(q) processes for arbitrary q (Meghir and Pistaferri (2004)). However, in administrative social security data it is plausible to assume that measurement error is sufficiently small to equate transitory movements in earnings with true worker level fluctuations in productivity. It is for this reason that the lack of evidence for purely transitory movement in earnings in both the IAB data and the Baker-Solon data, briefly mentioned above, can be interpreted as evidence that any earnings shocks have some persistence.

3.3 Estimation

The model generates theoretical autocovariances

$$\begin{aligned} \text{cov}(\widehat{y}_{ibt}, \widehat{y}_{ib,t+k}) &= p_t * p_{t+k} * \left\{ \left[\widetilde{\sigma}_\alpha^2 + (2h_{bt} + k) * \sigma_{\alpha\beta} + h_{bt} * (h_{bt} + k) * \sigma_\beta^2 \right] \right. \\ &\quad \left. + [\widetilde{\sigma}_{u_0}^2 + f^u(h_{bt}, \delta_0, \dots, \delta_{J_v})] \right\} \\ &\quad + \rho^k * \text{Var}(z_{ibt}) + 1(k=0) * \varphi_t^2 * \left(\sum_{j=0}^{J_\varepsilon} h_{bt}^j * \phi_j \right). \end{aligned} \tag{3.10}$$

where k is the order of the lag, $f^u(h_{bt}, \delta_0, \dots, \delta_{J_v})$ is a polynomial of order $(J_v + 1)$ that is linear in the δ'_j s, $1(k=0)$ is an indicator function for the variance elements, and the term $\text{Var}(z_{ibt})$ follows the recursion

$$\text{Var}(z_{it_0(b)}) = (\lambda_{t_0(b)})^2 * \sigma_{\xi_0}^2, \tag{3.11}$$

$$\text{Var}(z_{ibt}) = \rho^2 * \text{Var}(z_{ib,t-1}) + \lambda_t^2 * \left(\sum_{j=0}^{J_\varepsilon} h_{bt}^j * \gamma_j \right) \text{ for all } t > t_0(b). \tag{3.12}$$

In stationary models, equation (3.11) can be shown to have a closed-form solution that is highly nonlinear in model parameters. With factor loadings on the persistent shocks, the resulting process is nonstationary and does not have a closed-form solution. As a consequence, this expression has to be evaluated numerically.

In principle, one can estimate the model by matching M appropriately chosen moments, where M is the number of parameters. This is the approach commonly used to prove identification theoretically. However, it is statistically inefficient and selects the “targets” fairly arbitrarily. Hence, I follow the majority of the literature and adopt a Minimum Distance Estimator (MD). Let \widehat{C}_b be the estimated covariance matrix for a cohort born in year b . A typical element \widehat{c}_{btk} is the cohort-specific covariance between residual earnings in period t with residual earnings k periods apart. Collecting nonredundant elements of \widehat{C}_b in a vector $\widehat{C}_b^{\text{vec}}$ and stacking them yields the vector of empirical moments to be matched, denoted \widehat{C}^{vec} . Each element \widehat{c}_{btk} in \widehat{C}^{vec} has a theoretical counterpart described by (3.10). Denoting the parameter vector by θ and observables by Z , I write the stacked version of these *theoretical* autocovariance matrices as $G(\theta, Z)$. To be clear, Z is composed of observable objects entering equation (3.10), such as age, birth year, time, the lag, and various nonlinear functions of these variables. The (MD) estimator for θ solves

$$\widehat{\theta} = \underset{\theta}{\text{min}} [\widehat{C}^{\text{vec}} - G(\widetilde{\theta}, Z)]' W [\widehat{C}^{\text{vec}} - G(\widetilde{\theta}, Z)], \tag{3.13}$$

where W is some positive definite weighting matrix. As demonstrated by Altonji and Segal (1996), using W can introduce sizable small-sample biases, and it has become customary to use the identity matrix instead. In this case, $\widehat{\theta}$ in (3.13) becomes the Equally Weighted Minimum Distance Estimator (EWMD).

A seldomly used, though very useful result, is the equivalence between EWMD estimation and nonlinear least squares (NLS). I heavily rely on this equivalence in my discussion of identification because regression models have been studied extensively and

are commonly viewed as transparent and intuitive. It also guides how to estimate standard errors when autocovariance structures are large. To see equivalence of (EWMD) and (NLS), define the regression error $\hat{\chi}_{btk}(\tilde{\theta}, Z_{btk}, \hat{c}_{btk}) = \hat{c}_{btk} - G(\tilde{\theta}, Z_{btk})$. Here, \hat{c}_{btk} is an element in \hat{C}^{vec} uniquely determined by cohort, year, and lag. Similarly, $G(\tilde{\theta}, Z_{btk})$ is the theoretical counterpart, the nonlinear function of parameters and observables given by equation (3.10). The level of observation is *cohort-year-lag*. By definition, $\hat{\theta}$ solves

$$\hat{\theta} = \min_{\tilde{\theta}} \sum_{btk} \hat{\chi}_{btk}^2(\tilde{\theta}, Z_{btk}, \hat{c}_{btk}) \tag{3.14}$$

which is the (NLS)-estimation criterion, whereby one regresses autocovariances on the nonlinear parametric function $G(\theta, Z)$.

A consistent estimator of $\sqrt{\text{var}(\hat{\theta})}$, the standard error of the $\hat{\theta}$, is readily available, but depends on the matrix of fourth-order moments of residual earnings. This matrix has size $[\text{dim}(\hat{C}^{\text{vec}})]^2$. Given the length of my data and its administrative nature, using a consistent estimator is infeasible. Instead, I use cluster-robust standard errors of the NLS-estimator in (3.14), where clusters are defined by birth cohort. Since this involves data that are aggregated to the cohort-year-lag level rather than individual-level earnings panel data, there is clearly an information loss, and consistent estimation of $\sqrt{\text{var}(\hat{\theta})}$ will require additional assumptions. In the Appendix in the Online Supplemental Material (Hoffmann (2019)), I describe under which assumptions this approach delivers an asymptotically valid estimator of $\text{var}(\hat{\theta})$.

3.4 Identification

Viewing estimation of earnings processes via matching covariance structures through the lens of nonlinear least squares has one central advantage: Identification can be discussed in terms of concepts that are familiar from parametric regression models. Concepts such as omitted variable bias, control variables, or multicollinearity can be applied directly, and sufficient conditions for local point identification are readily available. The question of how to credibly identify slope heterogeneity can be answered by exploring if it produces any *unique* prediction on the data, that is, a prediction that is hard to generate by any other plausible mechanism. This is the central point I address in this section.

Since NLS and EWMD estimation are identical, the estimator $\hat{\theta}$ solves the system of $\text{dim}(\theta)$ first-order conditions

$$J_{\hat{\theta}}(Z)' * [\hat{C}^{\text{vec}} - G(\hat{\theta}, Z)] = 0, \tag{3.15}$$

where $J_{\theta}(Z) = \frac{\partial G(\theta, Z)}{\partial \theta'}$ is the Jacobian of $G(\tilde{\theta}, Z)$ at $\tilde{\theta} = \theta$, a matrix of size $\text{dim}(Z) \times \text{dim}(\theta)$. If the model structure is linear in parameters, that is, $G(\theta, Z) = Z' * \theta$, then the (NLS) estimator is equivalent to OLS: $\hat{\theta} = (Z' * Z)^{-1} * Z' * \hat{C}^{\text{vec}}$. Notice that the level of observation is an element in the covariance structure, *not* individual earnings.

For general nonlinear models, there is no closed-form solution, but sufficient conditions for local point identification and consistency of the NLS-estimator $\hat{\theta}$ have been established and are as follows:¹⁹

- (i) $p \lim(\hat{C}) = C$.
- (ii) $C = G(\theta, Z)$.
- (iii) $\text{rank}(J_\theta) = \dim(\theta)$.

Assumption (i) requires consistent estimation of the autocovariance structure, while assumption (ii) postulates that the model $G(\theta, Z)$ is correctly specified. The last assumption requires the Jacobian to have full rank at θ . Given that a consistent non-parametric estimator for the covariance structure is readily available, the first assumption is satisfied. One should thus view the second assumption as critical. For if the model $G(\theta, Z)$ is ill specified, the estimator $\hat{\theta}$ is inconsistent even if the rank condition (iii) is satisfied. Since the explanatory variables entering $G(\theta, Z)$ are usually limited to age, time, the order of the lag, and possibly education, model specification manifests itself in functional form restrictions on how these observables enter the model prediction. For example, a standard HIP model satisfies the rank condition, but as shown below, it is ill-specified because it inherently confounds estimates of slope heterogeneity with age effects in innovation variances. As a consequence, if one does not introduce age effects, condition (ii) is violated. The model (3.2) to (3.8) is particularly attractive from this point of view because it does not impose any arbitrary functional form restriction on the relationship between age or time and autocovariances.

To gain some intuition for the identification assumptions, it is helpful to notice that they have direct analogues in the theory of linear regression. Specifically, assumption (i) corresponds to a random-sampling assumption since this guarantees that the covariance structure C can be estimated consistently. Assumption (ii) corresponds to the linearity-in-parameters assumption combined with conditional independence of the error term. Indeed, as argued above, the EWMD estimator is the NLS estimator of the model

$$C^{\text{vec}} = G(\theta, Z) + \chi, \quad (3.16)$$

where χ is an i.i.d. error term. Finally, assumption (iii) implies that the explanatory variables cannot be perfectly collinear.

Now suppose that the model is well specified. As indicated by the notation above, it is assumed that the covariance structure is disaggregated to the cohort level. It is also assumed that recorded life cycles are sufficiently long for an order condition for identification to be satisfied.²⁰ Then the conditions for parametric identification have the following key implications:

¹⁹The equivalence between the NLS- and the EWMD-estimators is discussed in detail in [Cameron and Trivedi \(2005\)](#), Chapter 6.7, pp. 202–203. The conditions for local point identification are stated there as well.

²⁰The standard order condition for NLS estimation is satisfied as long as $\max\{J_\varepsilon, J_\nu, J_\xi\} < \max\{h_{bl}\}$. Recorded life cycles must be longer than the longest polynomial in age.

(Implication 1) The parameters $\tilde{\sigma}_\alpha^2$ and $\tilde{\sigma}_{u_0}^2$ cannot be separately identified. Inspection of equation (3.10) shows that $\tilde{\sigma}_\alpha^2$ and $\tilde{\sigma}_{u_0}^2$ enter the model additively, thus violating assumption (iii). This is a problem of multicollinearity. Intuitively, a random walk process changes individuals' intercepts permanently. If such a shock occurs immediately before labor market entry it cannot be distinguished from pre-labor market skills that are captured by α_i . In the following, I estimate a "combined initial condition" for the permanent component $\sigma_\alpha^2 = \tilde{\sigma}_\alpha^2 + \tilde{\sigma}_{u_0}^2$.

(Implication 2) If $\rho < 1$ all other model parameters are locally point identified. With a consistent estimator of C readily available, and under the assumption that the model is well specified, establishing identification requires checking the rank condition (iii). For general nonlinear models, this is difficult, especially if numerical computation or even simulation of $G(\theta, Z)$ is involved. However, for the class of earnings processes considered here it turns out to be quite straightforward because the model is "close to" linear in parameters. More specifically, apart from the AR(1) term, the theoretical covariance structure involves time fixed effects, polynomials in h_{bt} and k , and their interactions. The parameters of the model are coefficients on these terms. If $\rho < 1$ the AR(1) part of the model introduces some nonlinearity, which turns out to be crucial for identification as it guarantees that there is no perfect collinearity with the other terms. If $\rho = 1$, the AR(1) process generates a collinearity problem, and identification fails unless one imposes additional restrictions on the factor loadings. Details are given in Appendix C in the Online Supplemental Material.

Three points regarding this identification result are worth highlighting. First, it is common to prove identification of earnings processes by deriving a set of $\dim(\theta)$ equations involving the parameters and population moments that solve uniquely for θ . For the rich specification considered here, this is tedious. In contrast to this approach, I rely directly on the rank-condition for the EWMD-problem, where all, rather than $\dim(\theta)$, restrictions imposed by the model on the covariance structure are exploited. This does not only deliver tractability but also yields new insights as it clarifies which sources of variation identify which parameters. Second, it seems surprising that with just a few normalizations on factor loadings one can identify three sets of factor loadings and three sets of polynomials in age, ρ something that is impossible when estimating models of conditional first moments of earnings. The fundamental reason is that a life cycle of T periods provides only T first moments, but $\frac{1}{2} * T * (T + 1)$ autocovariance elements. As shown above and in Appendix C the behavior of off-diagonal elements as a function of the lag is a crucial source of identification. Third, intercohort variation, that is, variation in autocovariances conditional on calendar time and lag, is fundamental for establishing identification of both time and age effects at that level of generality. In practice, this requires covariance structures that are disaggregated to the cohort level, thereby imposing large demands on the data.

(Implication 3) Age profiles of variances are uninformative about HIP. Variances correspond to elements with $k = 0$. Equation (3.10) implies that their age profiles can be matched perfectly by allowing the polynomial $\sum_{j=0}^J h_{ibt}^j * \phi_j$, which is the transitory component, to have sufficiently high order. This means that any type of nonlinearity in age profiles of variances can be explained by age effects in the variance of transitory

shocks. Since there is no theory stating that dispersion of transitory shocks is constant over the life cycle, any a priori functional form restrictions on this component are arbitrary.

(Implication 4) Age profiles of high-order autocovariances are also uninformative about HIP. To see this implication, it is convenient to assume that $p_t = \lambda_t = 1$ for all t .²¹ If $\rho < 1$, one can use the fact that $\text{Var}(z_{ibt})$ is bounded above by $\max_{b,t}\{\text{var}(\widehat{y}_{ibt})\}$ to derive the following approximation for large k :²²

$$\text{cov}(\widehat{y}_{ibt}, \widehat{y}_{ib,t+k}) \approx \sigma_\alpha^2 + (2h_{bt} + k)\sigma_{\alpha\beta} + h_{bt} * (h_{bt} + k)\sigma_\beta^2 + f^u(h_{bt}, \delta_0, \dots, \delta_{K_v}). \quad (3.17)$$

Since $f^u(h_{bt}, \delta_0, \dots, \delta_{K_v})$ is a polynomial of degree $(K_v + 1)$ in h_{bt} that is linear in the δ_j 's, this expression is linear in parameters and can be estimated by OLS. None of the observables are multicollinear if h_{bt} and k vary across observations. All parameters entering this linear regression equation are therefore *globally* point-identified. However, holding k constant—corresponding to age-profiles of high-order autocovariances—does generate multicollinearity between the variables multiplying the parameters of the HIP component and the parameters of the heteroscedastic unit-roots process. This clarifies the special role of the lag profiles for identification.

(Implication 5) A credible source of identification of HIP are the tails of lag profiles. Slope heterogeneity imposes strong restrictions on the slope of lag profiles at large k , which can be used to develop an “eyeball” test for its relevance. Fixing h_{bt} at some arbitrary value and k at a large value, the difference of autocovariances between two lag values k and $k + n$ is given by

$$\text{cov}(\widehat{y}_{ibt}, \widehat{y}_{ib,t+k}) - \text{cov}(\widehat{y}_{ibt}, \widehat{y}_{ib,t+[k+n]}) \approx (n * \sigma_{\alpha\beta} + h_{bt} * n * \sigma_\beta^2). \quad (3.18)$$

The only parameters entering this expression are those for the HIP component, and they multiply variables that are not perfectly collinear. It is in this sense that HIP generates unique predictions on the tails of lag profiles. The restriction on the tails is important because the persistent AR(1) component can explain negatively sloped lag profiles at low orders. In contrast, if lag profiles at large k are downward sloping it must be the case that $\sigma_{\alpha\beta} < 0$. Furthermore, convexity can only be explained by $\sigma_\beta^2 > 0$. Conversely, if lag profiles converge to a constant, then $\sigma_\beta^2 \leq \frac{|\sigma_{\alpha\beta}|}{\max\{h_{bt}\}}$, which is likely to be very small. Combined, these results suggest that as long as empirical *lag profiles* do not display noticeable and robust convexities, slope heterogeneity is unlikely to be important even if *experience profiles* are convex.

In combination, these results show that the only credible source of identification of slope heterogeneity is the behavior of lag profiles at their tails. This is discouraging for two reasons. First, slope heterogeneity has the unique prediction that these tails are

²¹Relaxing this assumption does not have an effect on this implication.

²²Since $\widehat{y}_{ibt}^e = y_{ibt}^e - \mu_{bt}^e$, where μ_{bt}^e is the average log wage of cohort b with education e in period t , and since y_{ibt}^e is in logs, $|\widehat{y}_{ibt}^e|$ is rarely observed to be above 1 in *any* data set that is commonly used for the estimation of earnings processes. Hence, it is reasonable to assume that $\max_{b,t}\{\text{var}(\widehat{y}_{ibt})\} < 1$. In the sample used for empirical implementation of the model I find that $\max_{b,t}\{\text{var}(\widehat{y}_{ibt})\} < 0.5$. Thus, $\rho^k * \text{Var}(z_{ibt})$ will vanish quickly as k increases.

convex, which is a second-order feature of the empirical moments. Using consumption data in addition to earnings data will not overcome this issue because this prediction is generated by any heterogeneous agents model with a HIP earnings process. Second, the tails of lag profiles are constructed from earnings data for the same individual at two different points in time that are far apart. They are thus most likely affected by endogenous attrition. It is for this reason that I rely on the administrative IABS data in the empirical implementation since they have large sample size, partially addressing the first issue, and since they follow individuals for long periods of time because of administrative reasons, partially addressing the second issue.

The remainder of this section discusses some further issues via two examples.

EXAMPLE 3.1. Restricting the identifying variation for slope heterogeneity to the behavior of lag profiles at high orders can be achieved via controlling flexibly for age effects in innovation variances, as is the case for the earnings process (3.2)–(3.8). Conversely, if one does not allow for age effects even though they are important, then assumption (ii) is violated and slope heterogeneity will also be identified from the shape of age profiles, as discussed in Guvenen (2009). In this case, empirical estimates of the HIP component confound slope heterogeneity with age effects in variances of various types of shocks. This can be framed in terms of a classical omitted variable bias.

To illustrate this point, suppose that the true earnings process is a simple version of (3.2)–(3.8), described by

$$\begin{aligned}
 \widehat{y}_{ibt} &= \alpha_i + \beta_i * h_{bt} + u_{ibt}, \\
 u_{ibt} &= u_{ib,t-1} + v_{ibt}, \\
 \text{var}(\alpha_i) &= \widetilde{\sigma}_\alpha^2; \quad \text{var}(\beta_i) = \sigma_\beta^2; \quad \text{cov}(\alpha_i, \beta_i) = 0, \\
 \text{var}(v_{ibt}) &= h_{bt} * \delta_1; \quad \text{var}(u_{it_0(b)}) = 0.
 \end{aligned}
 \tag{3.19}$$

This combines a HIP model and a unit roots process with linear age effects in innovation variances. The autocovariance structure (3.10) reduces to

$$\text{cov}(\widehat{y}_{ibt}, \widehat{y}_{ib,t+k}) = \widetilde{\sigma}_\alpha^2 + \sigma_\beta^2 * [h_{bt} * (h_{bt} + k)] + \delta_1 * \left[\frac{h_{bt} * (h_{bt} + 1)}{2} \right].
 \tag{3.20}$$

This model is linear in parameters so that the EWMD estimator is equivalent to OLS. Estimation is performed on aggregate covariance structures, and I therefore drop the index i on the right-hand side. The level of observation is the k th order autocovariance in year t for individuals of birth cohort b .

Now suppose one erroneously neglects the age effect in innovation variances, corresponding to the a priori restriction $\delta_1 = 0$. Defining $z_{bt} = \frac{h_{bt} * (h_{bt} + 1)}{2}$, $x_{btk} = h_{bt} * (h_{bt} + k)$, and $\widehat{c}_{btk} = \widehat{\text{cov}}(\widehat{y}_{ibt}, \widehat{y}_{ib,t+k})$, the parameter estimate for σ_β^2 is given by $\widehat{\sigma}_\beta^2 = \frac{\sum_{btk} (x_{btk} - \bar{x}) * \widehat{c}_{btk}}{\sum_{btk} (x_{btk} - \bar{x})^2}$ and the omitted-variable bias formula for OLS implies that asymptotically

$$\widehat{\sigma}_\beta^2 - \sigma_\beta^2 = \delta_1 * \frac{\text{cov}(x_{btk}, z_{bt})}{\text{var}(x_{btk})}.
 \tag{3.21}$$

Since $\text{cov}(x_{btk}, z_{bt}) > 0$, the bias is positive if $\delta_1 > 0$: If variances increase over the life cycle quadratically due to an increase in the dispersion of permanent shocks, and if heteroscedasticity is not properly controlled for, then the EWMD estimator mistakenly assigns all of the convexity in the experience profile to the estimate of slope heterogeneity $\hat{\sigma}_\beta^2$.

EXAMPLE 3.2. It is helpful to demonstrate graphically the predictions of various model parts on the autocovariance structure. To this end, I compute theoretical experience profiles corresponding to various model components, using the parameter estimates from a similar model in Baker and Solon (2003).²³ Results are shown in the six panels of the Online Appendix, Figure 1. Each line in a panel represents the experience profiles of k th order autocovariances. The first panel plots the covariance structure implied by a random walk with a random effect. This is a line with intercept $\sigma_\alpha^2 = 0.134$ and slope $\delta_0 = 0.007$. In the second panel, I replace the random walk component by slope heterogeneity. With a relatively large estimate for $|\sigma_{\alpha\beta}|$, the experience profiles have negative slopes, while σ_β^2 introduces some convexity. The interaction between the lag and experience identifying σ_β^2 is reflected in high-order autocovariances having larger slopes in absolute value than low-order autocovariances. The third panel of the figure displays the covariance structure when one combines the first two panels. Given the large estimate for δ_0 , experience profiles are strictly increasing, and slope heterogeneity generates the convexity of these profiles and introduces a nontrivial relationship between autocovariances and the order of the lag. Next, I plot a homoscedastic AR(1)-process with a nonzero initial condition. The long-run value of its variance is given by $\frac{\gamma_0}{1-\rho^2} = \frac{0.09}{1-0.54^2} = 0.127$. Given that the initial condition $\sigma_{\xi 0}^2 = 0.167$ is larger than this value, convergence to the long-run value is from above, and the experience profile is convex. The next panel demonstrates experience profiles of autocovariances generated by a heteroscedastic AR(1) process with an initial condition. With the parameter values used, these profiles are convex and U-shaped. The final panel combines all five panels and demonstrates very clearly the points discussed above: The profiles are dominated by the properties of the AR(1) process at low lags, while they quickly converge to a lower envelope that is entirely dominated by the permanent component of the process. The final graph is remarkably similar to the empirical covariance structure used in the main part of my empirical analysis.

4. DATA AND DESCRIPTIVE ANALYSIS

4.1 Sample construction

How important quantitatively is the bias in estimates of slope heterogeneity when failing to properly control for age effects in innovation variances? This is an empirical question and requires data. The discussion of identification above suggests that two data

²³I compute experience profiles up to the largest potential experience level observed in their data, which is 33. The parameters values are taken from Table 4 in Baker and Solon (2003): $\sigma_\alpha^2 = 0.134$, $\sigma_\beta^2 = 0.00009$; $\sigma_{\alpha\beta} = -0.0031$; $\delta_0 = 0.007$; $\sigma_{\xi 0}^2 = 0.167$; $\rho = 0.54$; $\gamma_0 = 0.09$; $\gamma_1 = -0.005$; $\gamma_2 = 0.0001$; $\gamma_3 = 2.21 * \exp(-6)$; $\gamma_4 = 2.1 * \exp(-9)$. I set all factor loadings equal to one.

features are crucial for addressing this question convincingly. First, one requires panel data with many earnings observations per worker. Second, the attrition rate from the sample needs to be small. Optimally, one would also like to have a sample with an externally valid covariance structure. A data set that satisfies all of these requirements is the confidential version of the IABS, a 2% extract from German administrative social security records for the years 1975 to 2004. The IABS is collected by the German Federal Employment Agency and is representative of the population of workers who are subject to compulsory social insurance contributions or who collect unemployment benefits. This amounts to approximately 80% of the German workforce, excluding self-employed and civil servants. Once an individual is drawn, he is followed for the rest of the sample period.

A number of advantages of using these data instead of publicly available panel data or administrative panel data from other countries are worth discussing in some more detail. First, I can generate unusually long worker-specific earnings histories; I observe up to 120 earning records on the *quarterly* level for the same worker. Indeed, the spell-based sampling design of the IABS that allows construction of quarterly rather than annual panel data is one of its distinct features. Second, given the large number of observations in the sample I can construct *cohort-specific* covariance structures, enabling me to estimate models of second moments of residual earnings that allow for both age and time effects. This contrasts with studies relying on the PSID where small sample sizes require aggregation of autocovariances over cohorts. Third, since employees are observed from the time of labor market entry, I can flexibly model initial conditions of wage processes. Fourth, in contrast to North American administrative data, the IABS provides a well-defined education variable. Consequently, I can perform separate analyses for each education group because of the large sample sizes. Since covariance structures are quite different between these groups, I exploit this data feature to test the external validity and generalizability of my results. Importantly, the covariance structure of the largest education group strongly resembles covariance structures documented in various papers for the United States, Canada, and Great Britain, as discussed above. Fifth, earnings records are provided by firms under a threat of legal sanctions for misreporting and are unlikely to be plagued by measurement error.

There are also a number of drawbacks of the data, most importantly the top coding of earnings at the social insurance contribution limit, a structural break in the earnings records in 1984, and the lack of a variable that records the hours worked. Most of these issues can be addressed directly by applying sample restrictions that are common in the literature. First, I only keep full-time work spells for the main job held during a quarter to rule out that earnings dynamics are driven by hours changes along the intensive margin, and I drop individuals with unstable employment histories, defined as those who are absent from the data for at least 3 consecutive years.²⁴ Second, to minimize the frac-

²⁴The first restriction is similar to the hours restrictions used by most of the studies that rely on the PSID. See, for example, Haider (2001), Guvenen (2009), and Hryshko (2012). The IABS contains a variable recording whether the job is full- or part-time. In my sample of male employed workers who are observed on their main job held during a quarter, only approximately 2.5% of all spells are part-time. Here, the main job is defined as the job that generates the highest earnings during a quarter. The share of part-time workers

tion of top-coded earnings I drop highly educated workers, defined as those with a technical college or university degree. This leaves two large education groups, subsequently referred to as “high school dropout” and “high school degree” samples, with fractions of top-coded earnings observations that are low and similar to the ones in commonly used survey data.²⁵ Since top-coded earnings observations contain valid information, namely that an individual has a large positive earnings residual relative to some comparison group, I follow Haider (2001) and Card, Heining, and Kline (2013) in using an imputation procedure rather than dropping these observations.²⁶ Third, I use a novel and important sample restriction that only keeps individual labor market careers observed from labor market entry and, therefore, avoids an incidental parameters problem. Since earnings histories are left censored in 1975, I drop individuals who are observed in that year.²⁷ Some employees entering the labor market after 1975 do so at a fairly high age for possibly endogenous reasons. Hence, I only keep a sample of workers who start their career at education-specific mass points of age-at-labor-market-entry. These are 19 years for the high school dropout and 23 years for those with a formal secondary degree. Finally, I restrict the sample to male workers whose entire career is recorded in Western Germany. Due to fairly small sample sizes at the highest experience levels, I also drop observations for which experience exceeds 108 quarters in the secondary-degree sample and 100 quarters in the dropout sample. Further details of sample construction are given in Appendix A in the Online Supplemental Material.

4.2 Sample sizes

Sample sizes for the two education groups and for each cohort are reported in the left panel of the Online Appendix, Table 1. These are sums over both, individuals and time. As younger cohorts have shorter time series by construction of the sample, their sample sizes are significantly smaller than those for older cohorts. After imposing all sample restrictions, the oldest cohort in the secondary degree group, which is the education group I will focus on for reasons explained below, is born in 1955 and enters the labor

in the raw data, that is, before any sample restrictions are imposed, is 7.5% among male workers and 35% among female workers.

²⁵“High school dropouts” are individuals who do not obtain a formal secondary degree. “High school graduates” are defined as those who hold on to a formal secondary degree, including those with an apprenticeship degree. Because of the importance of the apprenticeship system in the German labor market, this group covers over 70% of the employed. The fraction of censored observations is 0.5% in the high school dropout sample and 4.7% in the high school degree sample. In comparison, it is 55.2% in the education group that is dropped from the sample.

²⁶A more common approach is to drop top-coded earnings records. This introduces a sample selection problem that potentially leads to a bias in the empirical autocovariances. In particular, with older workers being more likely to be at the top of the earnings distribution, dropping top-coded observations can lead to a downward bias in covariances between earnings early and late in the life cycle. It is therefore likely to lead to a downward bias in parameters that generate a fanning out of the wage distribution over the life cycle: Permanent shocks and slope heterogeneity. I have reestimated all specifications in this paper using this approach instead. The conclusions remain unaltered.

²⁷Labor market entry is defined as the period a worker has completed his highest degree and is recorded to have positive earnings. This drops apprenticeship spells from the data.

market in 1978. The oldest cohort in the other education group is born in 1957 and enters the labor market in 1976. In total, there are 4,752,287 income observations for the first and 414,231 income observations for the second education group. The right panel of the table reports sample sizes by experience in years instead. Approximately 323,000 individuals with a secondary degree are observed from their first year in the labor market, compared with 35,000 individuals for the other education group. Half of these entrants are still observed after 14 years for the first and 11 years for the second education group. In all cases, far more than 10% of the initial sample are still present after 20 years. Sample sizes decrease quickly as we approach the highest observed experience levels because less and less cohorts contribute to these observations. For example, only 3 cohorts reach an experience level of 24 years in the group with a secondary educational degree. In total, there are 824,962 earnings observations for these 3 groups. If there was no attrition, these groups should contribute $824,962/(24 + 1) = 32,998$ observations to each experience group. Given that over 26,000 observations are left after 24 years, the attrition rate is quite low.

4.3 Descriptive analysis

Estimation of Mincer earnings regressions with random coefficients and a dynamic error structure can be cast in terms of nonlinear least squares estimation on covariance structures, as argued above. Each parameter will thus be identified from some particular statistical variation in the empirical covariance structure. A detailed graphical analysis, carried out in this subsection, will give a first impression of the types of variation that are featured by the covariance structures.²⁸

Figure 1 plots autocovariances at different lags against potential experience h for the secondary degree group. Separate figures are provided for four different cohort groups, all of which display similar qualitative patterns in their covariance structures. First, autocovariances are converging gradually towards a positive constant as the lag increases, consistent with a random effects model that incorporates an AR process. Second, variance and autocovariance profiles at low lags decline over the first 20 to 30 quarters and increase slowly and steadily afterwards. As highlighted by Guvenen (2009) this convexity is consistent with heterogeneous returns to experience, that is, the “HIP component,” but it can potentially be generated by other mechanisms as well, such as age dependence in the innovation variances. Third, starting at a lag of approximately 20 quarters, the profiles become linear and strictly increasing, a possible evidence for the presence of a random walk component in earnings innovations. Fourth, earnings inequality as measured by the variance of log-earnings residuals is significantly larger for younger cohorts, and the same is true for higher-order covariances.

Earnings processes do not only have implications for the shape of life-cycle profiles of autocovariances, but also for the relationship between autocovariances and the lag, holding constant labor market experience. I present lag profiles at different levels of experience for the secondary-degree group in Figure 2. Again, I split the full sample into

²⁸Corresponding empirical first moments of log-labor income are listed in the Online Appendix, Table 2.

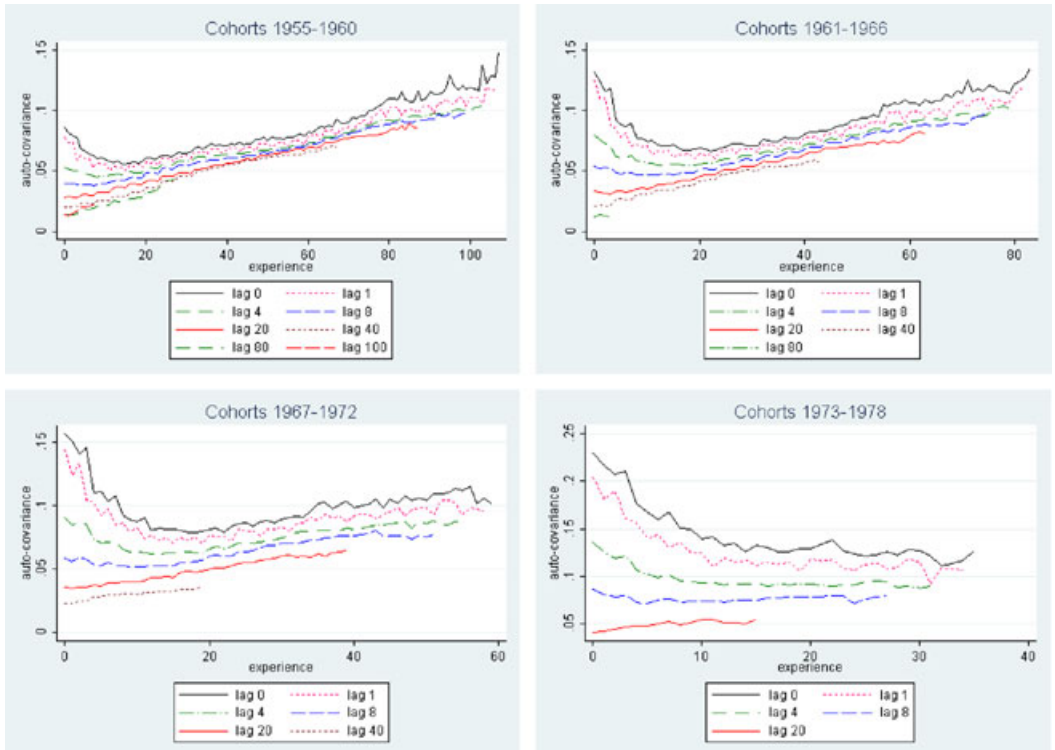


FIGURE 1. Life cycle profiles of autocovariances at different lags, by cohorts. Sample: Secondary Degree Group.

four cohort groups. Autocovariances are gradually and monotonically decreasing, eventually converging to some positive constant. Other than for small lags, the profiles for older workers within cohort lie significantly above those for younger workers.

A number of these empirical facts are consistent with the North American evidence. Guvenen (2009) documented a decrease of the variances over the first 5 years of a life cycle and an increase afterwards. Nonstationarity of the earnings structure, with a significant increase in the covariance structure over time and across cohorts, is also a well-known feature of North American data.²⁹ Negatively sloped lag profiles at low lags have been found in US earnings data as well, but there is some evidence that they are not monotonically declining for highly educated older workers.³⁰

The qualitative similarity of the covariance structure of German male workers with a secondary degree to the covariance structure reported in US data is the main reason for my empirical focus on this group. All empirical results for the dropout group are documented in the Online Appendix. As shown in the Online Appendix, Figures 2 and 3, the covariance structure for those without a secondary degree differs substantially from the covariance structure for the secondary-degree group. Most importantly, there is little ev-

²⁹See, for example, Gottschalk and Moffitt (1994), Haider (2001), Baker and Solon (2003), and Blundell, Pistaferri, and Preston (2009).

³⁰See, for example, Guvenen (2009).

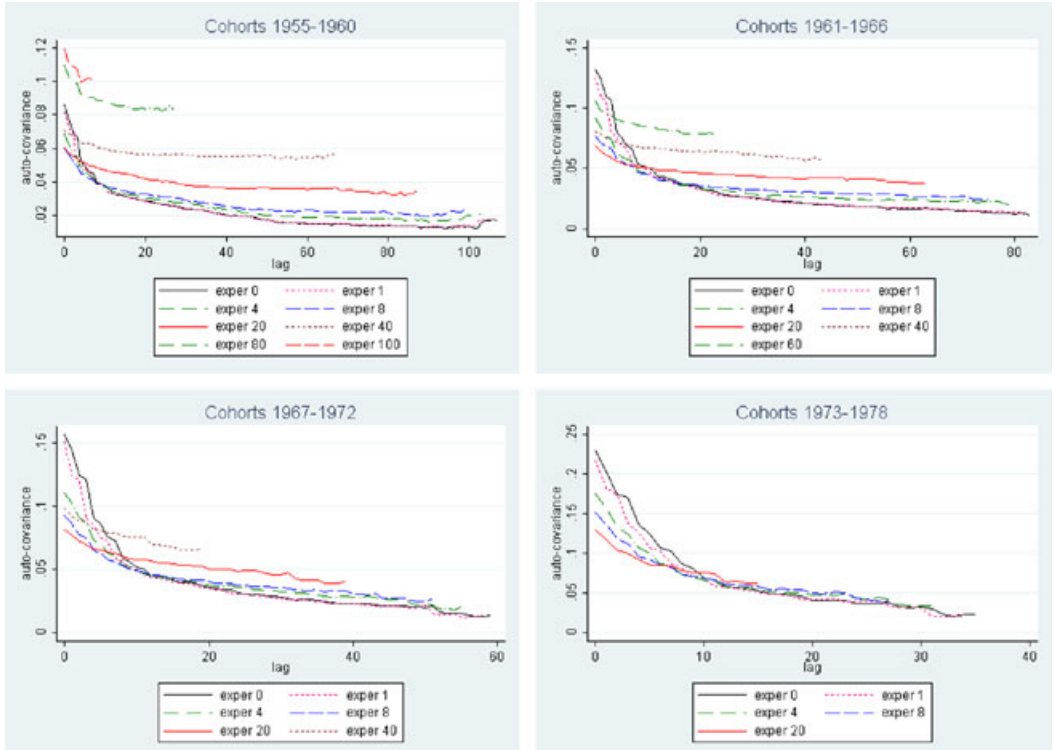


FIGURE 2. Lag profiles of autocovariances for different experience groups, by cohorts. Sample: Secondary Degree Group.

idence for convexities in the experience profiles, and convergence of experience and lag profiles takes place over the first 5 years of a career. High-order autocovariances are very close to zero and remain so for the entire life cycle. However, similar to the secondary-degree group, high school dropouts have experienced a significant fanning out of the wage structure as reflected in the increase of covariance profiles, but only early in the life cycle and at small lags. Hence, in contrast to the higher educated workers, there is a significant compression of the wage distribution over the life cycle for all cohorts.

5. EMPIRICAL RESULTS

In this section, I explore quantitatively how omission of age effects in innovation variances can affect estimates of profile heterogeneity. I start with showing that a slightly more restrictive model than (3.2) to (3.8) can be viewed as well specified in the sense that it fits the main empirical features of the covariance structure exceptionally well. This benchmark specification delivers estimates of slope heterogeneity that are not significantly different from zero. Afterwards, I demonstrate that imposing restrictions on this benchmark specification that are common in the literature dramatically alters this conclusion. I use Monte Carlo analysis to demonstrate that (i) the model parameters can be estimated precisely from data of the same size and structure as the IABS even if age

heteroscedasticity is modeled flexibly and that (ii) the central result of the paper that failing to control for such age effects produces substantial biases in estimates of HIP can be replicated in simulated data.

In the following, I focus my discussion on the results for the secondary-degree group since its covariance structure of earnings is qualitatively similar to the North American counterpart. I view the results for the high school dropouts, presented in the Online Appendix, as an extensive robustness check. A pretesting stage is required to determine the order of the age polynomials that govern the life-cycle variance dynamics of the process. This stage yields insignificant age effects for the unit roots process and the transitory component of the earnings process. This result can be anticipated from inspecting Figures 1 and 2. For the lower envelope of empirical age profiles is close to linear, consistent with a homoscedastic unit-roots process, and lag profiles are smooth around a lag of zero, suggesting that a transitory component is unlikely to be important.³¹ Given these results, I treat a specification that restricts $\delta_j = \phi_j = 0$ for all $j > 0$ in equations (3.6) and (3.8) as my benchmark. The parameters δ_0 and ϕ_0 can then be interpreted, respectively, as the variance of permanent and transitory shocks for *any* age group. In contrast, I find robust and significant age effects in the persistent component, and I use a polynomial of order 4, corresponding to $J_\xi = 4$ in equation (3.7).³²

5.1 *Estimates from the benchmark specification*

Parameter estimates for the benchmark specification are shown in the first column of Table 1 and, for the two sets of factor loadings, in the top panel of the Online Appendix, Figure 4.³³ The model fit is shown in Figure 3. Each of the panels plot theoretical against empirical autocovariances for four cohort groups, keeping constant the lag order.³⁴ The exercise is carried out for life-cycle profiles of autocovariances at a lag of 0, 4, 20, and 40 quarters. As can be seen from the figures, the model can generate qualitatively and quantitatively all the features of the autocovariance structure highlighted above, most importantly its evolution over the life cycle and over time. With EWMD estimation being equivalent to NLS, the R^2 is an informative summary measure of the goodness-of-fit. As can be expected from the graphical illustration, this value is very high: Over 96% of the variation in autocovariances can be explained by the model. This is quite remarkable given that I am matching 56,072 autocovariances with only 62 parameters.

³¹As discussed in the modeling section, this is also the reason why I am not including a MA(q)-component or factor loadings on the transitory component.

³²Increasing J_ξ does not improve the model fit significantly. One concern is that the Wald tests carried out in the pretesting stage, with the result that age effects in the variances of permanent and transitory shocks are jointly insignificant, have low power. I have investigated this issue using Monte Carlo analysis and found that this is not a problem. Importantly, the simulation results indicate that the estimator detects age heteroscedasticity in the distribution of permanent shocks if it is present in the data generating process. All results from the pretesting stage are available upon request.

³³The absolute value of $\text{corr}(\widehat{\alpha}_i, \widehat{\beta}_i)$ is contained in $[-1, 1]$ for all my estimates of $(\widehat{\sigma}_\alpha^2, \widehat{\sigma}_\beta^2, \widehat{\sigma}_{\alpha\beta})$. However, using the estimates displayed in the tables to calculate the correlation coefficient yields $\text{corr}(\widehat{\alpha}_i, \widehat{\beta}_i) < -1$ in some cases. This is due to rounding error.

³⁴An alternative would be to clean the autocovariances from cohort effects much like in the Online Appendix, Figure 1, but this would mask the ability of the model to fit intercohort changes.

TABLE 1. Parameter estimates for baseline specifications: secondary degree group.

		(1)	(2)
		Benchmark specification	No slope heterogeneity
Intercept heterogeneity	σ_α^2	0.023 (0.004)	0.012 (0.001)
Slope heterogeneity	$\sigma_\beta^2 * 10^3$	0.0005 (0.0014)	–
Cov (intercept; slope)	$\sigma_{\alpha\beta}^2 * 10$	–0.001 (0.0003)	–
Persistence of AR(1)	ρ	0.880 (0.006)	0.906 (0.005)
AR(1) error structure			
<i>Initial condition</i>	$\sigma_{\xi 0}^2$	0.092 (0.014)	0.080 (0.005)
<i>Intercept</i>	γ_0	0.007 (0.002)	0.004 (0.001)
<i>experience</i>	γ_1	–3.16 * e(–4) (1.17 * e(–4))	–1.49 * e(–4) (3.59 * e(–5))
<i>experience</i> ²	γ_2	7.68 * e(–6) (3.42 * e(–6))	3.18 * e(–6) (1.21 * e(–6))
<i>experience</i> ³	γ_3	–9.16 * e(–8) (4.63 * e(–8))	–3.73 * e(–8) (1.65 * e(–8))
<i>experience</i> ⁴	γ_4	3.95 * e(–10) (2.17 * e(–10))	1.61 * e(–10) (7.53 * e(–11))
Variance of permanent shocks	$\delta_0 * 10$	0.007 (0.001)	0.004 (0.001)
Variance of measurement error	ϕ_0	0.004 (0.001)	0.006 (0.001)
Number of moments			56,072
R^2		0.964	0.959
Wald test for slope heterogeneity (<i>P</i> -value)		0.000	–

Note: This table shows parameter estimates for the benchmark specification as described in equations (3.2) to (3.8) of the paper, together with a nested specification that sets slope heterogeneity to zero. Extensive pretesting indicated that age effects in the variances of transitory and permanent shocks are jointly insignificant. The benchmark specification thus allows for age effects in the variance of the persistent shocks only. Both specifications allow for factor loadings on the permanent and persistent component, all of which are significant on the 1% level. Estimated factor loadings for the full model are displayed in the first panel of the Appendix Figure 5. Standard errors are clustered by cohort to account for arbitrary correlation of sampling error within cohort-groups.

All parameter estimates but the variance of slopes, $\hat{\sigma}_\beta^2$, are significant on the 10%, and with few exceptions, on the 1% level.³⁵ There is substantial heterogeneity in the intercept and the initial condition of the persistent component, with estimated variances of $\hat{\sigma}_\alpha^2 = 0.023$ and $\hat{\sigma}_{\xi 0}^2 = 0.092$, respectively. The estimated persistence of shocks to the AR(1) process on the *quarterly* level is $\hat{\rho} = 0.88$, a fairly low value. Age effects in

³⁵This also applies to all factor loadings. To avoid clutter in the Online Appendix, Figure 3, I do not plot the confidence intervals.

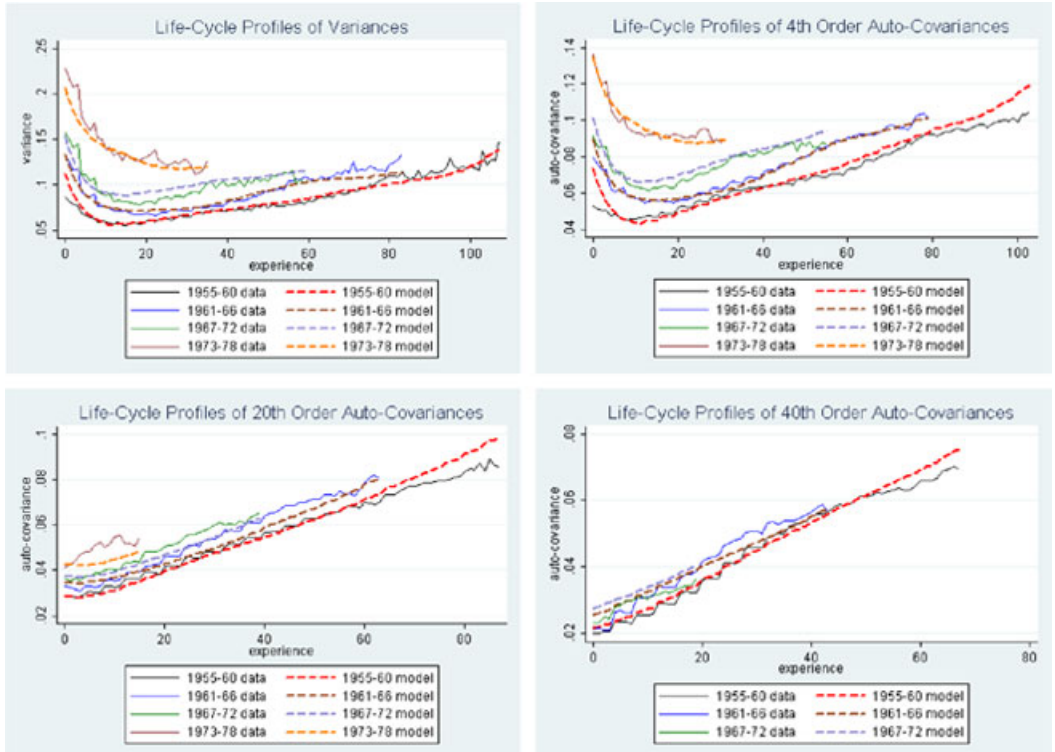


FIGURE 3. Fit of benchmark model: secondary degree group.

the variance of the persistent component as captured by the polynomial specification is estimated to be important, with all four coefficients on the monomials in experience being statistically significant. The variance of the transitory component, while statistically significant, is very small, with a value of $\phi_0 = 0.004$. Since both, the variance of earnings intercepts, $\widehat{\sigma}_\alpha^2$, and of the transitory component, ϕ_0 , translate one-to-one into log-earnings inequality, their magnitude can be directly related to overall log-earnings inequality. With a sample average of 0.094 for the 1488 variance elements in the autocovariance structure, the permanent component can explain approximately one quarter (0.023/0.094) of the total variation in log earnings in the group of the high school educated.³⁶

The evolution of the two sets of factor loadings plotted in the Online Appendix, Figure 4, helps identify whether the trend in the wage structure toward a higher level of income inequality is driven by an increase in the dispersion of the permanent or the persistent component. The empirical results are quite striking. Controlling for age, permanent inequality has remained almost unchanged, while persistent inequality has nearly quadrupled. As highlighted by Haider and Solon (2006), this implies that life-cycle inequality has grown much less than cross-sectional inequality.

³⁶The variance elements correspond to elements with a lag of zero ($k = 0$). Their range is [0.047, 0.266].

Turning to the HIP component, the estimated heterogeneity in slopes $\hat{\sigma}_\beta^2$ is insignificant on any conventional level and very small in magnitude, but its covariance with intercept heterogeneity $\hat{\sigma}_{\alpha\beta}$ is highly significant. At first sight, this finding is counterintuitive, but inspection of equation (3.10) clarifies that there is no intrinsic restriction by the model that forces $\hat{\sigma}_{\alpha\beta}$ to be insignificant whenever $\hat{\sigma}_\beta^2$ is. It is therefore important to document a test statistic for the *joint* significance of the two parameters, provided at the bottom of the table. The null hypothesis $(\sigma_{\alpha\beta}, \sigma_\beta^2) = (0, 0)$ is rejected on the 1% level.

The HIP hypothesis is about the heterogeneity of returns to human capital accumulation, σ_β^2 , and not about its covariance with the intercept term. Since the results in column (1) of the table do not provide any evidence in favor of this hypothesis, I also estimate the benchmark specification with the a-priori restriction $(\sigma_{\alpha\beta}, \sigma_\beta^2) = (0, 0)$. The estimates are listed in column (2) of the same table. The R^2 decreases by only 0.005, indicating that omission of the HIP component has no noticeable effect on the model fit. However, a number of estimates change substantially; most of all the variance of intercept heterogeneity $\hat{\sigma}_\alpha^2$, which decreases by a half to a value of 0.012.

Estimates of earnings processes commonly rely on annual, rather than quarterly data. I therefore compute the map from my parameter estimates to their annual counterparts, which does not have a closed form. To this end, I simulate quarterly worker-level panel data of log-earnings in a first step, using the model, its parameter estimates, and a data structure that is identical to the one in my sample. In a second step, I translate these data into earnings levels, aggregate them to the annual level, transfer them back into log earnings and estimate the model on the resulting covariance structure of *annual* log earnings. Results are shown in the Online Appendix, Table 3 for the main parameters of interest and for various specifications.³⁷ Estimates corresponding to column 1 of Table 1 are listed in column 1 of the Appendix table. The time-aggregated transitory component now has variance of zero since it is assumed to be *i.i.d.* across individuals, age, and time. The estimated intercept heterogeneity in the annual data is almost identical to its quarterly counterpart. In fact, if earnings were constant within a year, then the two estimates should be identical. The most interesting estimate coming out of this exercise is the persistence of the AR(1) process. On the quarterly level, this number has been estimated to be 0.88. As shown in the table, this translates into a persistence of 0.632 on the annual frequency.

5.2 HIP and age effects: Results from misspecified models

The discussion of identification above, in particular implications (4) and (5), predict that omission of age effects will yield inconsistent estimates of profile heterogeneity. This is a standard omitted variable bias because data variation that is consistent with various channels, such as age-dependent risk, contributes to identification of HIP. I now investigate the quantitative importance of this bias.

³⁷I do not show standard errors in this table since the data are generated exactly once under the assumption that the model is correctly specified and that sampling error is absent.

Parameter estimates for a standard HIP model as favored in the heterogeneous agent literature are shown in column (2) of Table 2. This is a model with intercept and slope heterogeneity, an AR(1)-process *without* an initial condition, a purely transitory component, and factor loadings on both persistent and transitory shocks.³⁸ There are no factor loadings for the HIP component. For a direct comparison with the benchmark specification, I reproduce its estimates in column (1) of the table. The discrepancy between the estimates of the two specifications is quite striking. Compared to the full model, profile heterogeneity as captured by $\hat{\sigma}_\beta^2$ is thirteen times as large and becomes highly statistically significant. The R^2 decreases dramatically to a value of 0.764, indicating that the model is severely misspecified. This is particularly remarkable given that the model still has 56 parameters, compared with 62 parameters in the benchmark specification. Another interesting result is that the estimated persistence of the AR(1) shocks is much larger in the HIP model than in the full model. In fact, it is not significantly different from one. This can be explained by the near linearity of experience profiles at high orders, which can be generated by a simple unit roots process. It follows that controlling for slope heterogeneity does not necessarily imply that shocks will be estimated to be less than persistent.³⁹

I also show results for a simple RIP model that does not have any time or age effects in column (3) of the table. Not surprisingly, this model delivers an estimated persistence that is much higher than in the benchmark model as well. The amount of variation in earnings associated with persistent and transitory shocks is much larger than in Guvenen's HIP model, with $\hat{\gamma}_0$ and $\hat{\phi}_0$ being substantially larger in in column (3) (RIP) than in column (2) (HIP) of the table. At the same time, intercept heterogeneity is much smaller in the RIP model. This demonstrates very clearly that the a-priori choice of an earnings process has first-order effects on the quantitative importance for earnings inequality one assigns to risk and to heterogeneity.

The next four columns of the table explore which components of the benchmark model have a particularly large effect on the estimates of the HIP component. I consider four nested versions of my benchmark specification: A model with homoscedastic shocks in column (4), a time-stationary model in column (5), a model without an initial condition for the AR(1) process in column (6), and a model that combines all of these restrictions in column (7). The last specification is equivalent to Hryshko's (2012) combined HIP-RIP process.⁴⁰ The conclusion one can draw from this analysis is quite clear. The HIP component is found to be significant only in specifications that do not feature an initial condition for the AR(1) process. This is a particular type of age effect, where one allows the variance of the persistent component to differ between labor market entrants and the rest of the employees. Its estimated importance for earnings dynamics is

³⁸The process is identical to the one estimated in Guvenen (2009). Importantly, this allows for factor loadings on the transitory component as well, which are found to be insignificant in my benchmark specification, but not in the more restrictive specification shown here.

³⁹Comparison with estimates in column 7 of the table clarifies that it is the introduction of a unit-roots component into the HIP process that has a major effect on $\hat{\rho}$.

⁴⁰The fit of Hryshko's (2012) model is lower than the fit of Guvenen's (2009) model because I consider a version of the former that excludes time effects.

TABLE 2. Robustness of parameter estimates: Secondary degree group.

	Full model, HIP, and RIP			Restrictions on benchmark specification			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Benchmark Specification	AR(1)—HIP (Guvonen)	Simple AR(1)	Homoscedastic	Stationary	Zero initial condition for AR(1)	Models (4)–(6) combined (Hryshko, stationary)	
Intercept heterogeneity	σ_α^2 (0.023 (0.004))	0.053 (0.004)	0.027 (0.002)	0.015 (0.001)	0.028 (0.003)	0.034 (0.004)	0.051 (0.004)
Slope heterogeneity	$\sigma_\beta^2 * 10^3$ (0.0005 (0.0014))	0.006 (0.003)	–	0.000 (0.001)	0.002 (0.002)	0.002 (0.001)	0.005 (0.002)
Cov (intercept; slope)	$\sigma_{\alpha\beta} * 10$ (0.0003)	–0.005 (0.0008)	–	–0.0006 (0.0001)	–0.002 (0.001)	–0.003 (0.001)	–0.005 (0.0007)
Persistence of AR(1)	ρ (0.880 (0.006))	0.996 (0.004)	0.982 (0.003)	0.905 (0.004)	0.857 (0.006)	0.755 (0.01)	0.757 (0.017)
AR(1) error structure							
<i>Initial condition</i>	$\sigma_{\xi_0}^2$ (0.092 (0.014))	–	–	0.081 (0.007)	0.136 (0.01)	–	–
<i>Intercept</i>	γ_0 (0.007 (0.002))	0.001 (0.0006)	0.002 (0.0002)	0.002 (4.31 * e(–4))	0.026 (0.007)	0.0212 (0.005)	0.011 (0.002)
<i>experience</i>	γ_1 (–3.16 * e(–4) (1.17 * e(–4))	–	–	–	–0.001 (2.75 * e(–4))	–0.002 (3.27 * e(–4))	–
<i>experience</i> ²	γ_2 (7.68 * e(–6) (3.42 * e(–6))	–	–	–	2.98 * e(–5) (1.02 * e(–5))	4.45 * e(–5) (8.86 * e(–6))	–
<i>experience</i> ³	γ_3 (–9.16 * e(–8) (4.63 * e(–8))	–	–	–	–3.67 * e(–7) (1.48 * e(–7))	–5.42 * e(–7) (9.93 * e(–8))	–
<i>experience</i> ⁴	γ_4 (3.95 * e(–10) (2.17 * e(–10))	–	–	–	1.64 * e(–9) (7.34 * e(–10))	2.29 * e(–9) (3.92 * e(–10))	–

(Continues)

TABLE 2. Continued.

	Full model, HIP, and RIP			Restrictions on benchmark specification			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Benchmark Specification		AR(1)—HIP (Guvenen)	Simple AR(1)	Homoscedastic	Stationary	Zero initial condition for AR(1)	Models (4)–(6) combined (Hryshko, stationary)
Variance of permanent shocks	$\delta_0 * 10$ 0.007 (0.001)	–	–	0.003 (0.001)	0.010 (0.001)	0.007 (0.001)	0.011 (0.0009)
Variance of measurement error	ϕ_0 0.004 (0.001)	0.018 (0.008)	0.026 (0.003)	0.000	0.003 (0.001)	0.001 (0.001)	0.005 (0.0006)
Number of moments							
R^2	0.964	0.764	0.592	0.919	0.803	0.889	0.738
Wald test for slope heterogeneity (P -value)	0.000	0.000	–	0.000	0.000	0.000	0.000

Note: This table explores the robustness of parameter estimates. Results for the benchmark specification as described in equations (3.2) to (3.8) are shown in column 1. Extensive pretesting indicated that age effects in the variances of transitory and permanent shocks are jointly insignificant. The benchmark specification thus allows for age effects in the variance of the persistent shocks only. Two specifications popular in the literature—a standard HIP-process as estimated in Guvenen (2009) and a simple RIP-process—are considered in the next two columns. The HIP-process allows for factor loadings on the permanent and the transitory (rather than the persistent) component. The four last columns explore the source of the sensitivity of parameter estimates by excluding various components from the full model: heteroscedasticity in column (4), factor loadings in column (5), an initial condition for the AR(1) process in column (6), and a combination of all these restrictions as considered in Hryshko (2012) in column (7). Standard errors are clustered by cohort to account for arbitrary correlation of sampling error within cohort-groups.

consistent with a large literature that documents a persistent impact of initial job placement on career advancement.⁴¹ At the same time, the result that its omission causes a potentially large upward bias in the estimated profile heterogeneity is new. It can be understood in terms of the discussion of identification in the previous section. Both model components can generate age effects in autocovariance profiles, in this particular case, a decline at the beginning of the life cycle. Once one does not control for the initial condition; all of this decline will be associated with slope heterogeneity, thereby biasing the estimate. In the full model, the two channels can be separated because the effect of the persistent initial condition eventually vanishes as experience and the lag increase, while the effect of slope heterogeneity becomes stronger.

5.3 Further analysis: Robustness and a Monte Carlo analysis

To explore further the interaction between controlling for age effects in innovation variances flexibly and the identification of HIP, I conduct two additional exercises. The first replicates the empirical analysis using a different sample, namely the workers in the IABS data who have no formal educational degree. The second investigates using Monte Carlo simulation on how well my estimation performs in finitely-sized samples. A detailed discussion of both exercises are included in Online Appendix E and F. Here, I briefly summarize the main findings.

How robust are the conclusions? Results from the high school dropout sample The results from estimating my benchmark specification on the sample of high school dropouts are documented in the Online Appendix, Table 4, which has the same structure as Table 2 for the main sample. Generally, the results are remarkably consistent with those found from the secondary-degree sample. In fact, they are even more extreme. The estimation of the benchmark specification delivers an estimate of zero for σ_β^2 , while it is highly significant when estimating the more restrictive HIP specification. These results are interesting because the covariance structures for the two samples are quite different, as discussed above. Hence, the *quantitative* results documented in this paper are unlikely to be an artifact of one particular data set, and thus should have external validity.

A Monte Carlo analysis One concern with my quantitative results is that the EWMD estimator may be poorly behaved in samples of finite size, especially if one models age-heteroscedasticity flexibly. In particular, empirically it may be hard to distinguish between HIP and age-heteroscedasticity since identification of the former relies on the tail behavior of lag profiles, which is a second-order feature of the data. I address this concern with a Monte Carlo analysis. The simulation protocol is described in Online Appendix F, and results are shown in the Online Appendix, Table 5. The main conclusion from this exercise is that a data set of the size of the IABS is sufficient to precisely estimate all model parameters. Most importantly, I do not find any systematic biases in

⁴¹See, for example, von Wachter and Bender (2006), Kahn (2010), Oreopoulos, von Wachter, and Heisz (2012), and Altonji, Kahn, and Speer (2016).

the estimates of HIP and the parameters describing age heteroscedasticity, and the sampling variance across 1000 Monte Carlo repetition is small relative to the magnitude of the true parameter values.

6. CONCLUDING DISCUSSION

The dispersion of individual returns to experience is an important parameter in life-cycle models of career- or consumption choices. It is common to estimate it by matching a HIP process to the empirical covariance structure of residuals from a Mincer earnings regression with random coefficients. In this study, I argue that such an approach to identification and estimation tends to produce an upward bias in profile heterogeneity if age effects in innovation variances are not controlled for. This is because the age structure of covariances is one source of identifying variation for slope heterogeneity in the absence of age heteroscedasticity, while various economic models suggest that the latter is an important source of life-cycle earnings variation. Once one models age effects semiparametrically, the only remaining identifying source for slope heterogeneity is the shape of the tails of lag profiles. It is here where profile heterogeneity makes particularly strong and unique empirical predictions.

The finding that heterogeneity in the returns to human capital accumulation needs to be identified from the joint distribution of earnings that are received many years apart may be discouraging, for two main reasons. On the one hand, lag profiles are most likely affected by endogenous sample attrition. On the other hand, patterns in the tails of lag profiles are second-order features of the data so that large sample sizes will be needed for precise parameter estimation. This however is not a methodological problem of matching autocovariances via EWMD or relying on earnings data only. Rather, it is a manifestation of the fact that it is difficult to statistically distinguish slope heterogeneity from other elements of earnings processes, such as heteroscedastic persistent shocks or a unit roots component. In practice, this means that data requirements for estimation of earnings processes are large, highlighting the importance of administrative data for future research.

While I have established theoretically that estimation of a HIP process without age effects in innovation variances will inevitably yield estimates of slope heterogeneity that are biased upwards, it is not clear a priori whether the bias is quantitatively important. To investigate this issue, I rely on German administrative data that follow workers for a long time and that record their earnings on the quarterly frequency, thus satisfying the large demands on the data. As my results show, the bias from omitting age effects can be substantial. In both samples, I am using, slope heterogeneity is found to be significant if I estimate a standard HIP model but turn insignificant and very small in magnitude when controlling for age effects. This is not due to larger standard errors in my benchmark specification, but because of a decrease in estimates, in my main sample by a factor of more than ten. Whether the bias is particularly large in the German data can only be answered with additional evidence from other countries. However, a number of findings that I document suggest that external validity is strong. First, qualitatively the autocovariance structure in the main sample shares many of the features of its North

American counterpart. This is reflected in estimates of standard RIP and HIP processes that are qualitatively similar to those obtained from US data. Second, as I have shown I reach the same conclusions for two very different autocovariance structures.

It is important to notice that my results do not imply that slope heterogeneity is unimportant generally. There may be samples and groups of workers for which the autocovariance structure of earnings is consistent with substantial profile heterogeneity. Instead, my results state that the HIP component will be estimated with an upward bias if age heteroscedasticity is not properly controlled for. This result carries over directly to any structural heterogeneous agents model in which individuals make choices about consumption or job search, as long as the underlying earnings process contains a HIP component. Hence, the behavior of the right tail of lag profiles of earnings covariances provide variation for a simple and powerful overidentifying test for HIP.

REFERENCES

- Abbott, B., G. Gallipoli, C. Meghir, and G. Violante (2018), “Education policies and intergenerational transfers in equilibrium.” *Journal of Political Economy*. (forthcoming). [1280]
- Abowd, J. M. and D. Card (1989), “On the covariance structure of earnings and hours changes.” *Econometrica*, 57 (2), 411–445. [1283, 1289]
- Alan, S., M. Browning, and M. Ejrnaes (2018), “Income and consumption: A micro semi-structural analysis with pervasive heterogeneity.” *Journal of Political Economy*. (forthcoming). [1285]
- Altonji, J., L. Kahn, and J. Speer (2016), “Cashier or consultant? Entry labor market conditions, field of study and career success.” *Journal of Labor Economics*, 34 (S1, part2), S361–S401. [1309]
- Altonji, J. and L. Segal (1996), “Small sample bias in GMM-estimation of covariance structures.” *Journal of Business and Economic Statistics*, 14 (3), 353–366. [1290]
- Altonji, J., A. Jr. Smith, and I. Vidangos (2013), “Modeling earnings dynamics.” *Econometrica*, 81 (4), 1395–1454. [1288]
- Alvarez, F. and U. Jermann (2000), “Efficiency, equilibrium, and asset prices with risk of default.” *Econometrica*, 68 (4), 775–798. [1280]
- Arellano, M., R. Blundell, and S. Bonhomme (2017), “Earnings and consumption dynamics: A nonlinear panel data framework.” *Econometrica*, 85 (3), 693–734. [1285]
- Baker, M. (1997), “Growth rate heterogeneity and the covariance structure of life cycle earnings.” *Journal of Labor Economics*, 15, 338–375. [1283]
- Baker, M. and G. Solon (2003), “Earnings dynamics and inequality among Canadian men, 1976–1992: Evidence from longitudinal income tax records.” *Journal of Labor Economics*, 6 (4), 445–469. [1284, 1288, 1289, 1296, 1300]

- Ben-Porath, Y. (1967), “The production of human capital and the life cycle of earnings.” *Journal of Political Economy*, 75 (4), 352–365. [1283]
- Biewen, M. (2005), “The covariance structure of East and West German incomes and its implications for the persistence of poverty and inequality.” *German Economic Review*, 15, 338–375. [1284]
- Blundell, R., M. Graeber, and M. Mogstad (2015), “Labor income dynamics and the insurance from taxes, transfers, and the family.” *Journal of Public Economics*, 127, 58–73. [1284, 1289]
- Blundell, R., L. Pistaferri, and I. Preston (2009), “Consumption inequality and partial insurance.” *American Economic Review*, 98 (5), 1887–1921. [1284, 1300]
- Bonhomme, S. and J.-M. Robin (2009), “Assessing the equalizing force of mobility using short panels: France, 1990–2000.” *Review of Economic Studies*, 76 (1), 63–92. [1285]
- Browning, M., M. Ejrnaes, and J. Alvarez (2010), “Modelling income processes with lots of heterogeneity.” *Review of Economic Studies*, 77 (4), 1353–1381. [1285]
- Browning, M. and M. Ejrnaes (2014), “The persistent-transitory representation for earnings processes.” *Quantitative Economics*, 5 (3), 555–581. [1285]
- Cameron, A. and P. Trivedi (2005), *Microeconometrics*. Cambridge University Press. [1292]
- Card, D., J. Heining, and P. Kline (2013), “Workplace heterogeneity and the rise of West German wage inequality.” *Quarterly Journal of Economics*, 128, 967–1015. [1298]
- Daly, M., D. Hryshko, and I. Manovskii (2017), “Improving the measurement of earnings dynamics.” Report, University of Alberta. [1284]
- Davis, S. and T. von Wachter (2012), “Recessions and the costs of job loss.” *Brookings Papers on Economic Activity*. [1288]
- De Nardi, M., G. Fella, and G. P. Pardo (2018), “Nonlinear household earnings dynamics, self-insurance, and welfare.” NBER working paper 24326. [1285]
- Dickens, R. (2000), “The evolution of individual male earnings in Great Britain: 1975–95.” *The Economic Journal*, 110, 27–49. [1284]
- Erosa, A., G. Kambourov, and L. Fuster (2016), “Towards a micro-founded theory of aggregate labor supply.” *Review of Economic Studies*, 83 (3), 1001–1039. [1280]
- Farhi, E. and I. Werning (2013), “Insurance and taxation over the life-cycle.” *Review of Economic Studies*, 80 (2), 596–635. [1280]
- Friedman, M. (1957), *A Theory of the Consumption Function*. Princeton University Press, Princeton, NJ. [1288]
- Fukushima, K. (2010), “Quantifying the welfare gain from flexible dynamic income tax systems.” Report, University of Wisconsin at Madison. [1280]

- Gottschalk, P. and R. A. Moffitt (1994), “The growth of earnings instability in the U.S. labor market.” *Brookings Paper on Economic Activity*, 25 (2), 217–272. [1284, 1300]
- Guiso, L., L. Pistaferri, and F. Schivardi (2005), “Insurance within the firm.” *Journal of Political Economy*, 113 (5), 1054–1087. [1288]
- Guvenen, F. (2007), “Learning your earning: Are labor income shocks really very persistent?” *American Economic Review*, 97 (3), 687–712. [1280, 1285]
- Guvenen, F. (2009), “An empirical investigation of labor income processes.” *Review of Economic Dynamics*, 12 (1), 58–79. [1280, 1283, 1295, 1297, 1299, 1300, 1306, 1308]
- Guvenen, F. (2011), “Macroeconomics with heterogeneity: A practical guide.” Federal Reserve Bank of Richmond Quarterly. [1280]
- Guvenen, F., F. Karahan, S. Ozkan, and J. Song (2015), “What do data on millions of US workers reveal about life-cycle earnings risk?” NBER Working Paper w20913. [1280, 1285, 1286]
- Guvenen, F., B. Kuruscu, and S. Ozkan (2014), “Taxation of human capital and wage inequality: A cross-country analysis.” *Review of Economic Studies*, 81 (2), 818–850. [1281]
- Guvenen, F. and A. Smith (2014), “Inferring labor income risk and partial insurance from economic choices.” *Econometrica*, 82 (6), 2085–2129. [1280, 1285]
- Haider, S. (2001), “Earnings instability and earnings inequality of males in the United States: 1967–1991.” *Journal of Labor Economics*, 19 (4), 799–836. [1280, 1283, 1297, 1298, 1300]
- Haider, S. and G. Solon (2006), “Life-cycle variation in the association between current and lifetime earnings.” *American Economic Review*, 96 (4), 1308–1320. [1280, 1304]
- Hall, R. E. and F. S. Mishkin (1982), “The sensitivity of consumption to transitory income: Estimation from panel data on households.” *Econometrica*, 50 (2), 461–481. [1284]
- Hause, J. (1980), “The fine structure of earnings and the on-the-job training hypothesis.” *Econometrica*, 48 (4), 1013–1029. [1283]
- Heathcote, J., K. Storesletten, and G. L. Violante (2005), “Two Views of inequality over the life-cycle.” *Journal of the European Economic Association*, 3, 765–775. [1284]
- Heathcote, J., K. Storesletten, and G. L. Violante (2008), “Insurance and opportunities: A welfare analysis of labor market risk.” *Journal of Monetary Economics*, 55 (3), 501–525. [1285]
- Heathcote, J., K. Storesletten, and G. L. Violante (2014), “Consumption and labor supply with partial insurance: An analytical framework.” *American Economic Review*, 104 (7), 2075–2126. [1280]
- Hirano, K. (2002), “Semiparametric Bayesian inference in autoregressive panel data models.” *Econometrica*, 70 (2), 781–799. [1285]

- Hoffmann, F. (2010), “An empirical model of life-cycle earnings and mobility dynamics.” Report, University of British Columbia. [1288]
- Hoffmann, F. (2019), “Supplement to ‘HIP, RIP, and the robustness of empirical earnings processes.’” *Quantitative Economics Supplemental Material*, 10, <https://doi.org/10.3982/QE863>. [1287, 1291]
- Horowitz, J. and M. Markatou (1996), “Semiparametric estimation of regression models for panel data.” *Review of Economic Studies*, 63, 145–168. [1285]
- Hryshko, D. (2012), “Labor income profiles are not heterogeneous: Evidence from income growth rates.” *Quantitative Economics*, 3, 177–209. [1283, 1297, 1306, 1308]
- Hryshko, D. (2014), “Correlated income shocks and excess smoothness of consumption.” *Journal of Economic Dynamics and Control*, 48, 41–62. [1285]
- Hu, Y., R. Moffitt, and Y. Sasaki (2018), “Semiparametric estimation of the canonical permanent-transitory model of earnings dynamics.” Report, Johns Hopkins University. [1285]
- Huggett, M. and G. Kaplan (2016), “How large is the stock component of human capital?” *Review of Economic Dynamics*, 22, 21–51. [1280]
- Huggett, M., G. Ventura, and A. Yaron (2011), “Sources of lifetime inequality.” *American Economic Review*, 101 (7), 2923–2954. [1281]
- Kahn, L. (2010), “The long-term labor market consequences of graduating from college in a bad economy.” *Labour Economics*, 17 (2), 303–316. [1309]
- Karahan, F. and S. Ozkan (2013), “On the persistence of income shocks over the life cycle: Evidence, theory, and implications.” *Review of Economic Dynamics*, 16 (3), 452–476. [1284]
- Krueger, D. and F. Perri (2006), “Does income inequality lead to consumption inequality? Evidence and theory.” *Review of Economic Studies*, 73, 163–193. [1280]
- Lamadon, T. (2016), “Productivity shocks, long-term contracts and earnings dynamics.” Report, University of Chicago. [1288]
- Lemieux, T. (2006), “Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?” *American Economic Review*, 96 (3), 461–498. [1284]
- Lillard, L. and Y. Weiss (1979), “Components of variation in panel earnings data: American scientists, 1960–70.” *Econometrica*, 47 (2), 437–454. [1283]
- Lochner, L. and Y. Shin (2014), “Understanding earnings dynamics: Identifying and estimating the changing roles of unobserved ability, permanent and transitory shocks.” NBER working paper 20068. [1285]
- Lopez-Daneri, M. (2016), “Life-cycle patterns of earnings shocks.” Report, Temple University. [1284]

- Low, H., C. Meghir, and L. Pistaferri (2010), “Wage risk and employment risk over the life-cycle.” *American Economic Review*, 100 (4), 1432–1467. [1280, 1288]
- MaCurdy (1982), “The use of time series processes to model the error structure of earnings in a longitudinal data analysis.” *Journal of Econometrics*, 18, 82–114. [1283]
- Meghir, C. and L. Pistaferri (2004), “Income variance dynamics and heterogeneity.” *Econometrica*, 72 (1), 1–32. [1283, 1285, 1289]
- Meghir, C. and L. Pistaferri (2011), “Earnings, consumption and life-cycle choices.” *Handbook of Labor Economics*, Vol. 4. [1280, 1285]
- Mincer, J. (1958), “Investment in human capital and personal income distribution.” *Journal of Political Economy*, 66 (4), 281–302. [1283]
- Mincer, J. (1974), *Schooling, Experience and Earnings*. National Bureau of Economic Research, New York, NY. [1280, 1283]
- Moffitt, R. A. and P. Gottschalk (2002), “Trends in the transitory variance of earnings in the United States.” *Economic Journal*, 112, C68–C73. [1284]
- Oreopoulos, P., T. von Wachter, and A. Heisz (2012), “The short- and long-term career effects of graduating in a recession.” *AEJ-Applied Economics*, 4 (1), 1–29. [1309]
- Pavan, R. (2011), “Career choice and wage growth.” *Journal of Labor Economics*, 29 (3), 549–587. [1288]
- Polachek, S. W., T. Das, and R. Thamma-Apiroam (2015), “Micro- and macroeconomic implications of heterogeneity in the production of human capital.” *Journal of Political Economy*, 123 (6), 1410–1455. [1288]
- Postel-Vinay, F. and H. Turon (2010), “On-the-job search, productivity shocks, and the individual earnings process.” *International Economic Review*, 51 (3), 599–629. [1288]
- Primiceri, G. and T. van Rens (2009), “Heterogeneous life-cycle profiles, income risk and consumption inequality.” *Journal of Monetary Economics*, 56 (1), 20–39. [1280]
- Sanchez, M. and F. Wellschmied (2017), “Modeling life-cycle earnings risk with positive and negative shocks.” Report, University of Bristol. [1284]
- Storesletten, K., C. Telmer, and A. Yaron (2004a), “Consumption and risk-sharing over the life-cycle.” *Journal of Monetary Economics*, 51, 609–633. [1280]
- Storesletten, K., C. Telmer, and A. Yaron (2004b), “Cyclical dynamics in idiosyncratic labor market risk.” *Journal of Political Economy*, 112, 695–717. [1284]
- von Wachter, T. and S. Bender (2006), “In the right place at the wrong time: The role of firms and luck in young workers’ careers.” *American Economic Review*, 96 (5), 1679–1705. [1309]

Co-editor Peter Arcidiacono handled this manuscript.

Manuscript received 2 April, 2017; final version accepted 21 November, 2018; available online 9 January, 2019.