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ABSTRACT

The Shift from Persistent Inequality to Earnings Instability in Belgium

Using rich administrative data from 2005 to 2021 for Belgium, this paper analyses how earnings dynamics differ across socio-demographic groups, focusing on gender and education. We find that while permanent earnings inequality remains the dominant source of overall earnings inequality in Belgium, it has declined modestly in recent years. We further decompose the sources of permanent inequality and find that this decline is mainly driven by reductions in between-group inequality, especially between men and women, and falling permanent earnings inequality among women. These factors combined, outweigh the disequalising effects from compositional shifts in the educational structure of the population. On the other hand, earnings instability has risen, particularly for the low- and medium-educated and more generally for men. These groups additionally exhibit higher persistence in transitory shocks. Our findings show that stability in overall inequality trends can mask structural changes in the nature of inequality, and highlights the importance of exploring the heterogeneity in earnings dynamics across skill groups.

JEL Classification: I24, J21, J31, J62

Keywords: earnings dynamics, education, Biewen decomposition

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1 Introduction

Rising inequality has been a central concern across advanced economies, yet its underlying sources differ substantially. A key distinction, first emphasised by the influential work of Gottschalk and Moffitt (1994)[1] , is between permanent inequality (i.e., persistent, long-run differences in earnings) and earnings instability (i.e., short-run, mean-reverting fluctuations). These components have distinct welfare and policy implications: while persistent inequality reflects structural differences in opportunities and returns to skills, instability relates more to income risk and vulnerability, with consequences for consumption smoothing, savings, and social protection.

Much of the early literature has focused on North America, documenting rising inequality driven by increases in permanent earnings differences, with more mixed evidence on transitory components in the United States (Moffitt et al., 2023; Baker, 1997; Baker and Solon, 2003; Beach et al., 2010; Carr and Wiemers, 2018). For Europe, evidence has been more limited and heterogenous, partly due to differences in data and methods (Sologon and O'Donoghue, 2009, 2014).[2] From the 1990s to early 2000s, rising earnings inequality was driven by increases in both components in Finland (Kässi, 2014), Sweden (Gustavsson, 2008; Domeij and Flodén, 2010), Germany (Bartels and Bönke, 2013; Daly and Valletta, 2008) and the United Kingdom (Dickens, 2000; Kalwij and Alessie, 2007; Ramos, 2003), while Luxembourg (Sologon and Van Kerm, 2018) and Italy (Cappellari, 2004) experienced increases in permanent inequality alongside declining earnings instability. Spain experienced trends similar to Luxembourg and Italy, but with an overall decline in inequality (Cervini-Plá and Ramos, 2012).

Despite the growing availability of administrative data, studies covering more recent periods in Europe are scarce and show that the nature of inequality may have changed in some countries, reflecting again the substantial heterogeneity in the literature. Tomelleri (2022) finds a change in trends from 2010 in Italy: permanent inequality decreased slightly while earnings instability rose. From 2010 to 2015, Gustafsson and Holmberg (2023) find contrastingly now a decreasing trend in both components for Sweden compared to the increases in the 90s. Although general trends are hard to pin down across different periods, much of the literature documents a rise in earnings instability among younger cohorts (Cappellari, 2004; Ramos, 2003; Cervini-Plá and Ramos, 2012; Gustafsson and Holmberg, 2023). Such patterns align with growing global concern over earnings volatility and, more broadly, economic insecurity in the context of shifting employment relations and recent financial crises (Brewer et al., 2025).

At the same time, these concerns raise the question of whether certain groups are more exposed to risks than others. For one, several studies have investigated whether trends in inequality relate to differences in earnings dynamics across skill groups.[3] Trends and persistence of the different components of earnings tend to differ by education levels, as well as over the life-cycle (Blundell et al., 2025, 2015; Gustafsson and Holmberg, 2023). Findings from this research consistently show that inequality among higher-educated groups is driven by persistent earnings differentials, whereas among the less educated, earnings instability plays a larger and growing role (Meghir and Pistaferri, 2004; Gottschalk and Moffitt, 1994; Bartels and Bönke, 2013; Hryshko, 2012).[4] More importantly, permanent shocks, and even transitory shocks, may not be fully insurable for the less educated (Blundell et al., 2008).[5] Understanding the heterogeneity in earnings dynamics across skill groups is therefore crucial, as differential exposure to and insurance against shocks play a role in shaping long-run inequality and mobility.

This paper adds to the literature by exploiting a rich and unique administrative dataset covering Belgium from 2005 to 2021. Cross-sectional indicators show that inequality has remained low and stable in Belgium,

[1]The literature dates as early as Lillard and Willis' (1978) seminal work on earnings mobility.

[2]See also, the Global Repository of Income Dynamics (GRID) project, which uses administrative data along with graphical methods to examine income dynamics across several countries, including a large number of European states (Guvenen et al., 2022).

[3]A number of studies have also looked at other dimensions, such as differences between natives and migrants (Sologon and Van Kerm, 2018), occupations (Cappellari, 2004), insurance membership (Bingley et al., 2013), as well as tenure and contract-type (Cappellari and Leonardi, 2016; Tomelleri, 2022).

[4]This relationship has also been found for combined spousal earnings and family income (Hryshko and Manovskii, 2018; Ludwig, 2015).

[5]More specifically, Blundell et al. (2008) find in the US that permanent shocks are uninsurable for less educated individuals, and that transitory shocks are only partially insured for low-income households. See also Friedrich et al. (2019), who examine whether firm-specific permanent and that transitory shocks are transmitted to earnings of workers across education levels.

with a steady decrease in the gender pay gap (Assal et al., 2022; Capéau et al., 2024; Valenduc, 2017; Decoster et al., 2019). Our paper aims to uncover whether this apparent stability conceals underlying changes in permanent and transitory earnings dynamics, whether these dynamics differ across gender and education groups, and whether compositional shifts in the educational structure of the labour force affect changes in permanent inequality.

In addressing these questions, we make three main contributions. First, the longitudinal nature of the administrative data and a long panel length allow for an in-depth study into the dynamics of earnings in Belgium, which to our knowledge, has not been done before.[6] We add to the limited but growing body of research on earnings dynamics in Europe, covering a more recent period which includes the 2008 financial crisis and COVID-19 crisis. By focusing on Belgium, our study complements existing work by offering insights from a country with strong labour market institutions that differ markedly from the US and other liberal market economies. Second, we explore how earnings dynamics differ by gender and education subgroups, delineations that have not been sufficiently explored in the earnings dynamics literature, often due to data limitations faced in earlier studies.[7] Third, we innovate by applying the Biewen (2014) approach to decompose permanent inequality trends, allowing us to disentangle compositional shifts in the labour force from changes in within- and between-group inequality.

Belgium offers a particularly compelling case in this regard. Its institutional architecture, near-universal collective bargaining coverage, automatic wage indexation, and a historically stable reform trajectory (Marx and Van Cant, 2019), has produced one of the most compressed wage distributions in Europe. Yet, beneath this stability, several vulnerabilities persist: growing labour dualism between standard and non-standard contracts, the over-representation of women in part-time and atypical work, and persistent risks of poverty among the low-educated, migrants and single-parent households (Nautet and Piton, 2019; OECD, 2020; Gonne, 2022). Cross-sectional inequality trends may therefore obscure the likely heightened and higher levels of instability experienced by these vulnerable subpopulations over the years.

Education is a key factor that could explain this differential exposure to risks. Despite the "massification" of education, studies have highlighted that access to tertiary education in Belgium remains undemocratised (Vanderstraeten and Van der Gucht, 2023; Kruithof and Verhaeghe, 2024). Consistent with this, Belgium exhibits one of the highest degrees of intergenerational persistence in educational inequalities and one of the lowest levels of social mobility at school among OECD countries (Gonne, 2022).[8] At the same time, low-skilled workers face growing insecurity as they are increasingly displaced by medium-skilled workers in low-skilled jobs (OECD, 2020), which may explain why the low-skilled are more likely to be employed in volatile, non-standard work (Marx and Van Cant, 2019). Although non-standard work is not prevalent in Belgium[9], the higher incidence of temporary contracts among the low-skilled raises concerns about their increasingly disadvantaged position, given that intermittent earnings often limit access to contribution-based social security benefits. Concurrently, there has been a compositional shift in the low-educated population away from women and towards men (OECD, 2020), alongside an increase in men taking up part-time work and temporary contracts.

Altogether, the aforementioned developments and features of the Belgian labour market underscore the relevance of our research questions. In line with these aims, our findings reveal a shift in the structure of earnings inequality in Belgium. While permanent earnings inequality remains the dominant source of overall inequality in Belgium, it has declined modestly in recent years, largely due to decreasing between-group inequality and inequality within women. These factors outweigh the disequalising effects from

[6] One of the few comparative studies in the literature, Sologon and O'Donoghue (2009), examines male earnings dynamics in 14 EU countries using European Community Household Panel (ECHP) survey data from 1994–2001, including Belgium. They find that both earnings instability and permanent inequality in Belgium fell during this period. The overall decrease in total inequality was driven by a stronger decline in permanent inequality.

[7] The earnings dynamics of women is often not studied in older papers from the literature, due to the endogeneity associated with female labour market participation. More recently, however, studies have included women due to higher participation rates in contemporary times. See, for example, Holmberg (2024) and Kässi (2014). Based on data from the European Union Labour Force Survey (EU-LFS), the labour force participation rate of women of working age (25-59) in Belgium has increased only slightly from 74.9% to 79.6% in 2005 and 2021 respectively.

[8] There are also increasing regional disparities between Flanders, Wallonia and Brussels, with the latter two regions featuring higher shares of early school leavers (Vanderstraeten and Van der Gucht, 2023).

[9] Part-time employment, on the other hand, is common, especially among women, and more prevalent in Belgium relative to the rest of the EU (Nautet and Piton, 2019).

a compositional shift in the educational structure of the labour force. In contrast, earnings instability has increased for the average mid-career worker, especially among the low- and medium-educated. Low-educated men, in particular, are the only subgroup whose within-group earnings inequality is driven primarily by earnings instability. These groups, in addition, face higher persistence in transitory earnings shocks. Our findings raise important questions about the role of policy in addressing earnings instability for these subgroups, given the higher risks of poverty and social exclusion that they face.

The remainder of the paper proceeds as follows. Section 2 presents our data and methodology. In Section 3, we begin with descriptive analyses, and thereafter discuss the main parameter estimates of our models, overall trends in permanent inequality and earnings instability, and subsequent decompositions. We end this section by checking the business cycle sensivity of our results. Finally, Section 4 concludes.

2 Data and empirical approach

2.1 Data

The data is constructed from linked administrative data sources provided by Statistics Belgium (Statbel) for the period between 2005 and 2021, inclusive. The microdata contains *individual*-level socio-demographic data (annually from the demographic database DEMOBEL and from a limited number of census years), tax return data (IPCAL) as well as some social security data. Information on earnings is obtained from tax forms. Monetary values are not top-coded but are rounded by a factor for confidentiality. To account for inflation, the monetary values are deflated by the Consumer Price Index (CPI) with 2021 as the base year.

The income concepts available from administrative data quite notably differ from that of survey data such as the EU-SILC. For one, the available income concepts are *net taxable* and are not strictly gross amounts.[10] The available earnings data that we make use of is gross earnings that has been deducted by social security contributions (SSC).[11] As we do not have information on hours worked, we focus on earnings dynamics and not wage dynamics.

Despite this limitation, the value of the currently available administrative data should not be overlooked. The large numbers and longitudinal nature of the dataset enable earnings dynamics, for the first time, to be studied in Belgium. Other available sources, namely survey data such as the EU-SILC or the Labour Force Survey (LFS), are mostly cross-sectional, only have categorical income data, or have panel lengths that are too short for the identification of permanent earnings and therefore, cannot provide reliable estimates. Income data from tax returns is also more reliable than in the EU-SILC (at least before the use of administrative data in the survey from 2019), as there has been evidence of underreporting in the survey from matched SILC-IPCAL data (Decoster et al., 2014). As such, measurement error is neglible.[12] Further, attrition is limited to deaths and migration.[13]

[10]The biggest issue to consider here regarding the use of quasi-net earnings is the Social Work Bonus (SWB) – a system that came into effect in the year 2000 with the aim of preventing unemployment traps, where low-wage employees who otherwise would be subject to a SSC rate of 13.07% receive a compensation to their SSC via a (tapering) lump sum, leading to an effective reduction of their SSC rates to about 2-4% of their gross salaries. We argue, however, that the SWB would have a small to almost negligible effect on the conclusions drawn from our results. Studies evaluating the SWB find that it has a positive impact on employment rates. Nevertheless, the size of the SWB is still too small to have a large impact (Vandelannoote and Verbist, 2019). Further, during the period studied, changes to this system have been gradual and fairly minor since its inception (Dewatripont and López Novella, 2024).

[11]This includes ordinary remuneration as well as tips and certain benefits-in-kind (company cars, phone subscriptions, telework and internet allowances), excluding professional expenses. However, benefits-in-kind such as ecocheques as well as meal vouchers are excluded.

[12]Income from undeclared or informal work is not captured and falls beyond the scope of this paper.

[13]Using the death register, individuals are excluded from the sample in the year of their death. Unfortunately, the data does not allow for capturing attrition fully from in-and-out migration.

2.2 Sample

A 10% simple random sample of tax-filers is first obtained, and then subsequently linked to the other administrative data sources through pseudonymised identifiers.[14] The sample is then further restricted by age. In each given year, we include only individuals who are of working age, defined as the ages between 25 and 59 inclusive. In doing so, we limit the inclusion of students and early entrants of the labour market, as well as pensioners. We exclude the self-employed by strictly including individuals who only report salaried earnings. Additionally, we exclude individuals in years where pension income exceed earnings, as well as employees of international organisations who are tax-exempt. For years that individuals do not meet the sample requirements, their earnings are regarded as missing.

In order to model and estimate the earnings process for an individual, a minimum of two data points (i.e., non-zero tax declarations) is required. Individuals with less than two years of reported earnings are thus excluded. Evidently, this is a relatively lax requirement. To ensure that our results are not biased by the inclusion of workers with weak attachment to the labour market, we only include individual-years of earnings above an income threshold of 1/3 the annual minimum income of a full-time employee.[15]

2.3 Methodology

2.3.1 The canonical error-components model and common specifications

To fix ideas, we begin with a simple error-components model of earnings. First, we detrend earnings by subtracting subgroup means from individual earnings.[16] We calculate demeaned earnings for subgroups based on gender and education.[17] Correspondingly, demeaned earnings, y_{it} is then denoted as the sum of a permanent and transitory component:

$$y_{it} = \alpha_i + \nu_{it} \tag{2.1}$$

where α_i is the time-invariant individual-specific permanent component, representing fixed characteristics (i.e., unobserved ability or skills), and ν_{it} is the transitory component, representing short-term fluctuations away from an individual's earnings profile over time (e.g., due to temporary job loss or illness).

It is assumed that the two components are *i.i.d.* with mean zero and are orthogonal to each other (i.e., $E(\alpha_i) = E(\nu_{it}) = E(\alpha_i \nu_{it}) = 0$). The transitory component is assumed to be serially uncorrelated, allowing for identification. Using the additive decomposability of the variance, the share of total residual inequality (i.e., variance of residual earnings) attributable to permanent shocks is then simply the ratio of the variance of the permanent component to the sum of the variance of both components, $\sigma_\alpha^2 / \left(\sigma_\alpha^2 + \sigma_\nu^2\right)$ (Moffitt and Gottschalk, 2011).

Evidently, Equation (2.1) represents a simplistic random effects model. In truth, the permanent component is permanent in the sense that it reflects shocks that are *persistent* and are therefore non-mean-reverting, while transitory shocks fade out over time. In other words, the transitory component is assumed to only be serially uncorrelated with sufficiently long lags. Thus, by using the observed autocovariance structure of (residual) earnings over a lengthy panel, one can estimate the contribution of the two components from identifying first the variance of the permanent component and then obtaining the variance of the transitory

[14] Our results are qualitatively similar when using a proportional stratified random sample balanced by birth cohort, gender and region.

[15] This is based on the general minimum monthly wage for an employee working 38 hours a week, calculated to an annual amount.

[16] An alternative approach would be to residualise earnings by regressing on a set of observable characteristics. A first-stage regression and cohort-demeaning are both standard approaches in the literature (Meghir and Pistaferri, 2010). We also performed separate estimations with residual earnings obtained by regressing the logarithm of annual earnings yearly on a set of age and education dummies. The estimated parameters from the models we run using regressed earnings do not differ substantially from our results using demeaned earnings. We ultimately decided on the demeaning approach, similar to Baker and Solon (2003), Sologon and Van Kerm (2018) and Gustafsson and Holmberg (2023), as this approach is less restrictive.

[17] Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions. "Low" refers to the completion of lower secondary education or below. "Medium" refers to the completion of secondary education or post-secondary non-tertiary education. "High" refers to the completion of tertiary education.

component as a residual:

$$
\begin{aligned}
\operatorname{Cov}(\nu_{it}, \nu_{is}) &= 0, \quad \text{with } t \neq s && (2.2)\\
\implies \operatorname{Cov}(y_{it}, y_{is}) &= \operatorname{Cov}(\alpha_i + \nu_{it},\, \alpha_i + \nu_{is}) \\
&= \operatorname{Var}(\alpha_i) = \sigma_\alpha^2 && (2.3)\\
\sigma_\nu^2 = \operatorname{Var}(\nu_{it}) &= \operatorname{Var}(y_{it}) - \sigma_\alpha^2 && (2.4)
\end{aligned}
$$

In the following subsections, we present common modifications applied to the canonical model in the literature that reflect a more realistic earnings process before arriving at our final specified model.[18]

Time- and cohort-specific shifters

Often in the literature, the importance of the earnings components is allowed to realistically vary over time and across birth cohorts by including time- and cohort-specific loading factors (Haider, 2001):

$$y_{it} = q_c p_t \alpha_i + s_c \lambda_t \nu_{it} \tag{2.5}$$

where q_c and s_c are cohort-specific shifters for cohort c, and p_t and λ_t are time-specific shifters in period t for the respective components as denoted above. Allowing for variation across cohorts is important, as it captures, for instance, differences across cohorts in terms of skills and returns to education. The time-specific shifters control for macro-level influences such as recessions and other business cycle fluctuations. The shifters are normalised to one in the first period to allow for identification.

Permanent process with a random walk

On top of the above loading factors, the structure of the two components has also been modeled to reflect more realistic earnings processes based on economic theory. In particular, there is empirical evidence for most countries showing the persistence in the dispersion of earnings over the lifecyle. In the literature, the permanent component is often modeled therefore as a random walk or with random growth (Guvenen, 2009).[19] A random walk (Equation (2.7)) reflects shocks that permanently affect future earnings. Examples would be job promotions or demand shifts in the industry leading to abrupt changes in the returns to skills or education. The model in (2.5) then becomes:

$$
\begin{aligned}
y_{it} &= q_c p_t(\alpha_i + \mu_{it}) + s_c \lambda_t \nu_{it} && (2.6)\\
\mu_{it} &= \mu_{i,(t-1)} + w_{it} && (2.7)
\end{aligned}
$$

where μ_{it} follows a random walk and w_{it} is a white noise error term.

Permanent process with heterogeneous growth rates

Alternatively (or additionally), one can model the permanent component using random growth rates, where shocks are moderately persistent. Consistent with the theory of human capital accumulation, individuals have heterogeneous growth rates (denoted below as β_i in Equation (2.8)) in their earnings profiles, representing different skill premiums and life-cycle growth rates that accumulate with (potential)

[18] More recently, the literature has focused on methodological innovations such as building multivariate models (e.g., combining income and consumption), and more flexible models that allow for non-linearity as well as non-normality in the earnings process (Altonji et al., 2023; Meghir and Pistaferri, 2010). Both univariate and multivariate models are typically estimated using parametric methods, but non-parametric methods (e.g., window averaging and graphical analyses of higher order moments) have also been used. To maintain cross-comparability and parsimony, our paper uses univariate models.

[19] A random walk model and random growth model are also referred to in the literature as Restricted Income Profiles (RIP) and Heterogeneous Income Profiles (HIP) respectively.

labour market experience or age, x_{it} (Baker, 1997).

$$y_{it} = q_c p_t(\alpha_i + \beta_i x_{it}) + s_c \lambda_t \nu_{it} \tag{2.8}$$

The fixed term, α_i can be seen as initial earnings prior to labour market entry, which can be correlated with the growth rate, β_i. If the covariance between initial earnings and the growth rate, $\sigma_{\alpha\beta}$, is negative, it reflects a trade-off between human capital investment (e.g., schooling and on-the-job training) and experience. Individuals who forego higher initial earnings are then able to catch-up eventually with higher growth rates (Mincer, 1984). On the other hand, if $\sigma_{\alpha\beta}$ is positive, this suggests that individuals with higher initial earnings have higher growth rates due to greater productivity – such is consistent with matching models and job ladders, where the match quality between workers and firms and the workers' productivity are revealed over time (Cappellari, 2004).

Transitory process with serial correlation

In the canonical model, transitory shocks are assumed to have no impact on earnings in the next period. However, in reality, transitory shocks may have some degree of persistence and/or significant but short-lived effects. Think, for instance, about unexpected economy-wide shocks such as the COVID-19 pandemic that created temporary job losses. The serial correlation of transitory shocks is often specified in the literature as an AR(1) or ARMA(1,1) process, with ϵ_{it} representing white noise (Moffitt and Gottschalk, 2011).

$$\text{AR}(1): \quad \nu_{it} = \rho \nu_{i,(t-1)} + \epsilon_{it} \tag{2.9}$$

$$\text{ARMA}(1,1): \quad \nu_{it} = \rho \nu_{i,(t-1)} + \theta \epsilon_{i,(t-1)} + \epsilon_{it} \tag{2.10}$$

The autoregressive parameter, ρ, in the above equations captures the degree of persistence (or rate of decay), where transitory shocks to earnings in the current period affect earnings in subsequent periods but with a gradual diminishing effect. The moving average parameter, θ, captures immediate effects of a shock that translate into the next period but not in subsequent periods after. Due to the recursive nature of v_{it} and because some individuals are not observed throughout their working histories, the literature often follows MaCurdy (1982) by estimating the initial variance of the transitory shock.

2.3.2 Model specification and estimation

Empirical autocovariance structure

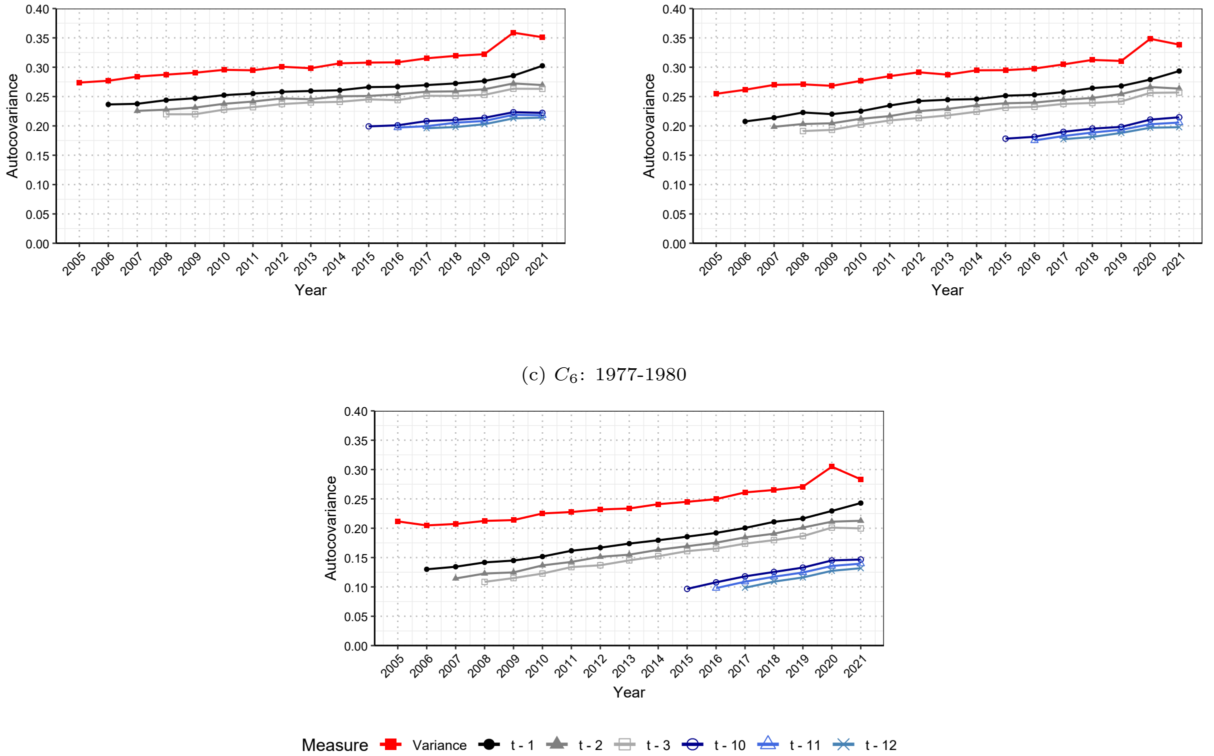
To determine if the common specifications in Section 2.3.1 also apply to Belgian earnings, we calculate the empirical autocovariance matrices for each cohort. For brevity, we show autocovariance graphs for only the youngest (C_1), middle (C_3) and oldest (C_6) cohorts.[20]

The variance in residual earnings for both cohorts and across genders, as depicted in Figure 1, appears to be increasing over time (i.e., with age/experience). According to Guvenen (2009), a concave ($\rho < 1$) or linear ($\rho = 1$) trend in age in the variance of earnings could suggest the presence of an AR(1) process in permanent earnings. We see mostly a linear trend in the variance across all cohorts, suggesting the presence of a random walk in permanent earnings.

To isolate year effects, we additionally plot autocovariances by age in Figure 2, keeping the year fixed, for a select number of years.[21] From the graphs, the variance of earnings generally follows a linear trend in age. Permanent earnings in Belgium thus likely follow a random walk rather than a random growth model according to our data. In both Figures 1 and 2, the autocovariance plots also show that there is serial correlation in earnings even at higher order lags. Based on the sudden drop from the first lag ($t-1$) to

[20] Autocovariance plots for all cohorts are available in Figure C1 in Appendix C.
[21] Autocovariance plots for all years are available in Figure C2 in Appendix C.

Figure 1. Within-cohort autocovariances



(a) C_1: 1962-1964

(b) C_3: 1968-1970

(c) C_6: 1977-1980

Note: The autocovariances of log residual earnings refer to $\text{Cov}(t, t-k)$, where k refers to the lag.

the second lag $(t-2)$ autocovariances, as well as the gradual decay in subsequent autocovariances, we can deduce that transitory earnings are likely to follow an ARMA(1,1) process (Moffitt and Gottschalk, 2011).

Model specification

Based on these autocovariance plots, we thus specify an error-components model including time- and cohort-specific shifters, a permanent component that incorporates a random walk as well as a transitory component that follows an ARMA(1,1) process.[22] Cohort-demeaned earnings in our main specification is thus modeled as:

$$y_{it} = q_c p_t(\alpha_i + \mu_{it}) + s_c \lambda_t \nu_{it}, \tag{2.11}$$

where

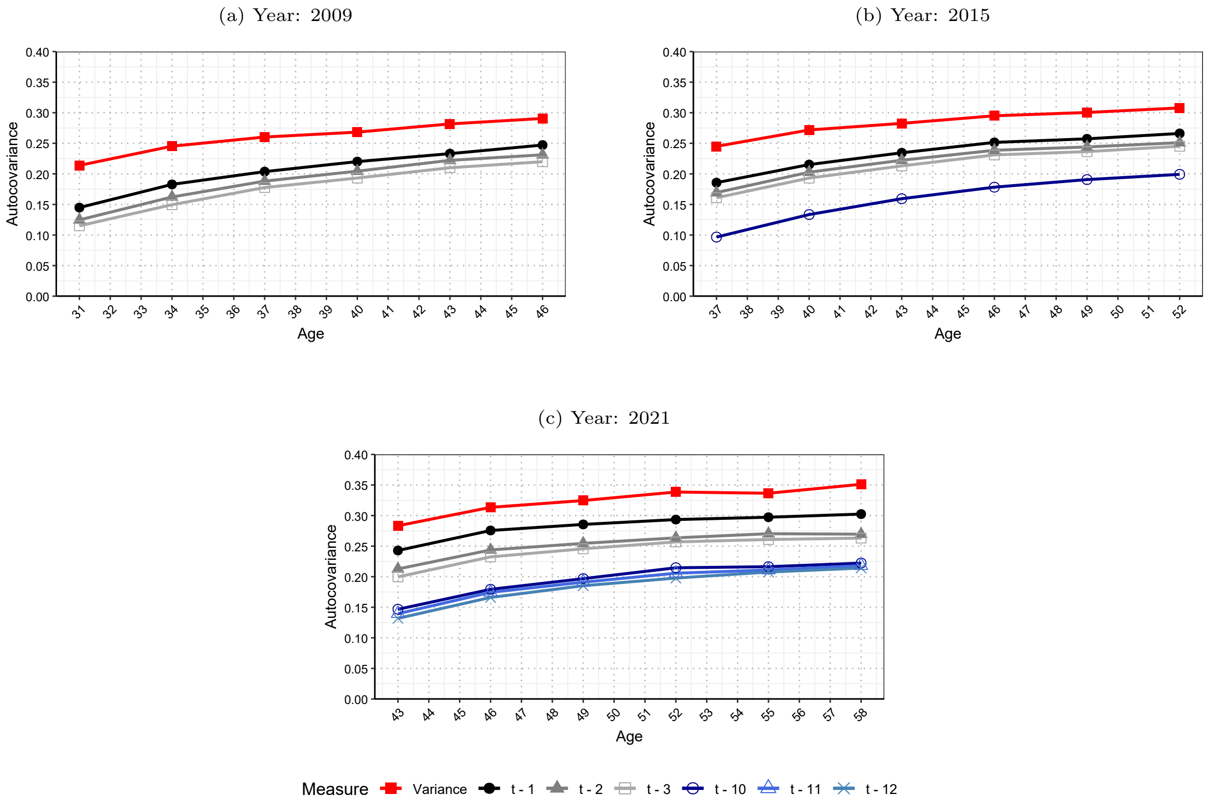
$$\mu_{it} = \mu_{i,(t-1)} + w_{it}, \tag{2.12}$$
$$\nu_{it} = \rho \nu_{i,(t-1)} + \theta \epsilon_{i,(t-1)} + \epsilon_{it}, \tag{2.13}$$

and

$$\begin{aligned} \alpha_i &\sim \text{i.i.d.}(0, \sigma^2_\alpha), \\ w_{it} &\sim (0, \sigma^2_w), \quad \nu_{i1} \sim (0, \sigma^2_{\nu 1}), \quad \epsilon_{it} \sim (0, \sigma^2_\epsilon), \\ i &= 1, \ldots, N, \quad t = 1, \ldots, T, \quad c = 1, \ldots, C. \end{aligned}$$

[22] For robustness, we also performed the estimation using a combined random growth and random walk model in permanent earnings. As expected, we did not find significance and the correct sign in the growth slope, β. We also ran a model with only random growth in permanent earnings, which did not converge.

Figure 2. Autocovariances by year



Note: The autocovariances of log residual earnings refer to $\text{Cov}(t, t-k)$, where k refers to the lag.

The vector of parameters, ϕ, to be estimated include the time- and cohort-specific shifters $(q_c, p_t, s_c, \lambda_t)$, the variance of individual-specific heterogeneity (σ_α^2), the variances of the permanent shock (σ_w^2) and transitory shocks $(\sigma_{\nu 1}^2, \sigma_\epsilon^2)$, as well as the autoregressive (ρ) and moving average (θ) parameters.

To limit bias from censoring in the estimation of cohort effects, only cohorts observed during the entire observation period are studied.[23] We do allow, however, for an unbalanced panel at the individual-level by allowing individuals to exit and re-enter the panel. As only individuals with positive earnings throughout the observation period would contribute to the estimation in a balanced panel, an unbalanced panel prevents overestimating the permanent component of earnings.

With the working age range of 25 to 59 inclusive, this means we only include individuals born between the years 1962 and 1980, yielding a total of 188,747 individuals and a total of 3,208,699 individual-year observations that meet the basic sample requirements mentioned in Section 2.2.[24]

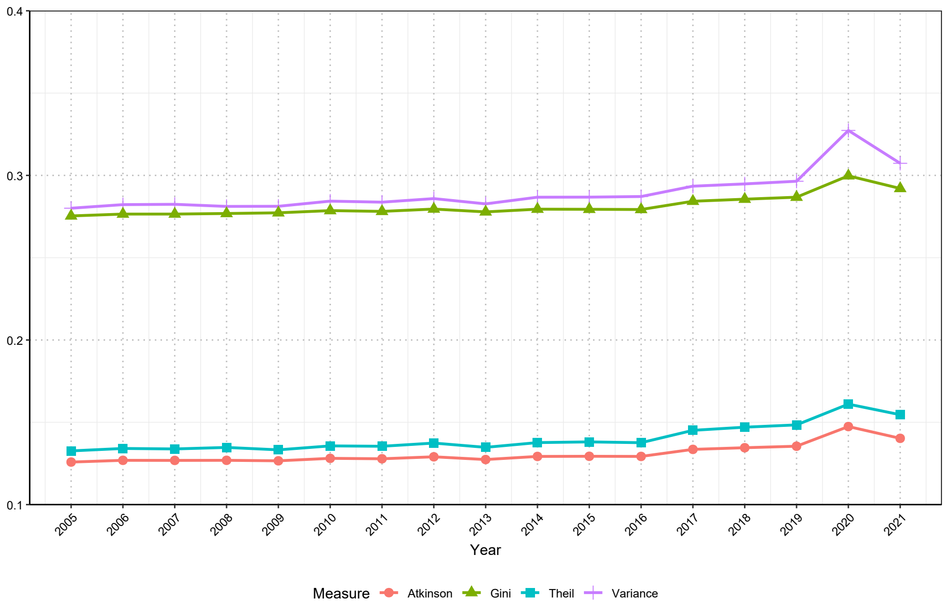
Model estimation

We use Generalised Method of Moments (GMM) to obtain estimates of the aforementioned parameters in Equations (2.11)–(2.13). From the model specification, the theoretical structure of the variance-covariance matrix is derived for each three-year birth cohort (see Appendix A.1). The cohort matrices are then stacked. The parameters are estimated through Equally Weighted Minimum Distance (EWMD) by using the identity matrix as the weighting matrix, where the distance between the theoretical moments and empirical moments (i.e., sample analogues) from the data is minimised (Altonji and Segal, 1996). Standard errors are calculated using the approach in Haider (2001).

[23] Due to computational limitations, we group cohorts into three-year birth cohorts, resulting in six groups.

[24] A breakdown of the number of observations per gender and per birth cohort group is provided in Table B1 in Appendix B. The number of observations per gender-education subgroup and per birth cohort group is available in Table B2.

Figure 3. Earnings inequality among employees of working age in Belgium, 2005-2021



Note: The figure shows different inequality indices calculated on the entire 10% sample that is of working age (between the ages of 25 and 59 inclusive) who report only salaried earnings that are positive and above three times the minimum wage. Atkinson (1), Gini and Theil indices are calculated on real gross earnings. Variance is calculated on *log* real gross earnings. Figure C3 in Appendix C shows the evolution of inequality including the self-employed.

3 Results

3.1 Descriptive analyses

We begin by examining cross-sectional trends in earnings inequality in Belgium among the entire working age sample of employees from 2005 until 2021. Figure 3 shows a variety of inequality indices graphed over time – Atkinson (1), Gini, Theil and the variance. The first three indices are calculated on the basis of real gross earnings, while the variance is calculated using the logarithm of real gross earnings.

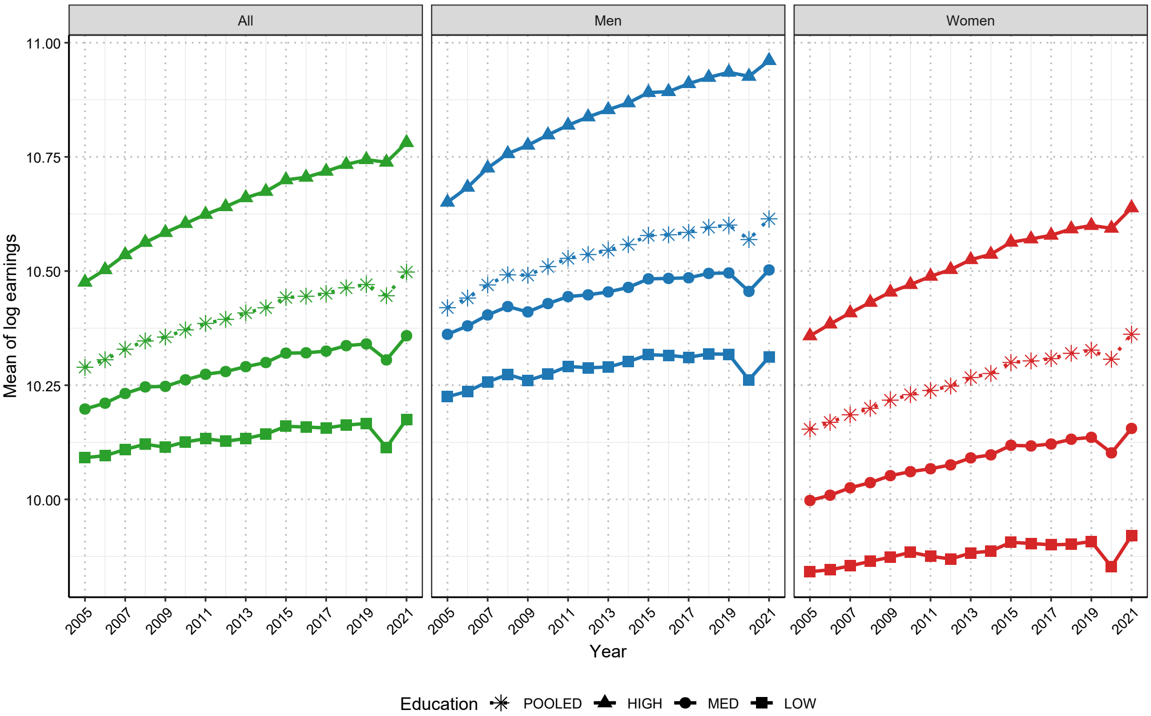
Overall, between 2005 and 2021, earnings inequality appears low and stable, with a very slight upward trend between 2015 and 2019 and a sharp increase in 2020, due to a recession fueled by the COVID-19 pandemic, where Belgium faced a negative 5.3% growth in GDP (World Bank, 2024). Specifically, the Gini of gross earnings increased from 0.319 in 2014 to 0.329 in 2020.[25] The Atkinson (1) and Theil indices, which are more bottom- and top-sensitive respectively, as well as the variance, follow similar trends.

In Figure 4, we graph the mean of log earnings of employees by gender as well as different education subgroups – low, medium and high, where low education refers to lower secondary education and below, medium education refers to the completion of secondary education, and high education refers to tertiary education. During the period 2005 to 2014, when earnings inequality was stable, the mean of log earnings across all education subgroups grew at a similar rate, albeit at a steeper slope for the highly educated.

Since 2015, coinciding with a slight rise in inequality, we see that for the low and medium educated, average earnings plateaus while earnings of the highly educated continue to grow. The earnings gap between medium and low educated individuals, however, has remained quite stable. Subsequently, in 2020, we observe a general dip in earnings that is more pronounced for the lower educated subgroups, indicating that these groups were more affected by the recession following the COVID-19 pandemic. This was indeed the case as low-skilled workers, who are predominantly employed in sectors disproportionately affected by the pandemic, faced the highest incidences of (long-term) temporary unemployment (OECD, 2020). Lastly, women in the lower education groups appear to have the lowest level of earnings and earnings

[25]This increase resembles the slight increase and levels found in the same period using the Gini of gross income from the OECD IDD (Assal et al., 2022).

Figure 4. Mean of log earnings by gender and education



Note: The figure shows the mean of log earnings calculated among employees of working age (between the ages of 25 and 59 inclusive). Employees are workers who report only salaried earnings in the entire observation period. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

growth.

The above provides some indication that the rising trend in inequality since 2014 may be explained partially by differences in earnings growth by education, although we cannot differentiate the extent this is due to hourly wage rates or hours worked. Capéau et al. (2024) also find that inequality between education subgroups has not only been increasing since the 1980s, but also in more recent times (between 2006 and 2020) in Belgium. However, they caution that part of this increase is not only due to widening wage differentials but also to increasing shares of the highly educated in the population. Such could perhaps signify that younger cohorts have different compositional shares in education subgroups, with a rising share of highly educated individuals.[26]

Figure 5 zooms further into the variance of *demeaned* earnings *within* gender and education subgroups. Although the overall level of earnings inequality within women is generally higher than that of within men, they both follow similar trends during the observed period. When we disaggregate by education subgroups, we find that the level and trends in within-group inequality of women do not differ significantly across educational backgrounds. The level of within-group inequality for highly educated men, however, is strikingly high. Trends in within-group inequality, on the other hand, remain similar for men across the different education levels. In the following sections, we explore more formally how earnings dynamics evolve within and across gender and education levels.

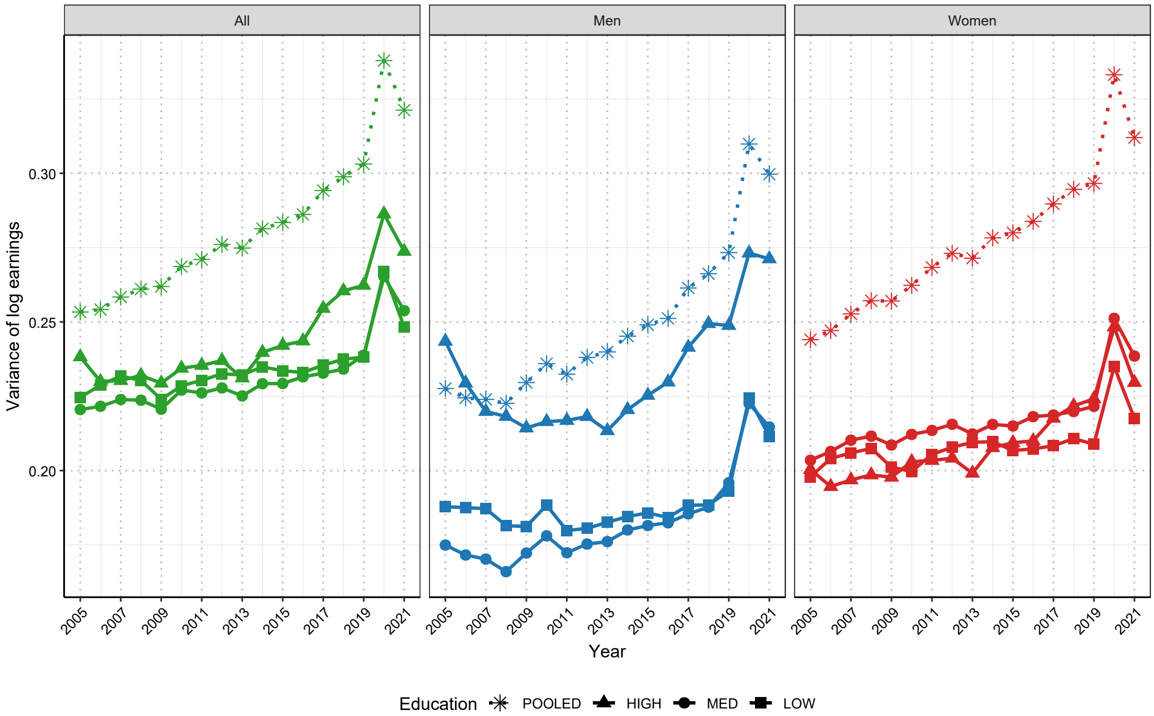
3.2 Main parameter estimates

Table 1 shows the main parameter estimates of the models.[27] We estimate earnings processes separately by subgroup: for the entire sample, for men and for women, and for men and women disaggregated by

[26] Additionally, our data for employees shows that younger cohorts have increasingly higher educational attainment (see Figure C4 in Appendix C). There has been a striking increase in the share of the tertiary-educated among younger women relative to men.

[27] The estimates of the time- (Tables B3, B4, B5 and B6) and cohort-specific shifters (Tables B7 and B8) are available in Appendix B.

Figure 5. Variance of gross employee earnings by gender and education



Note: The figure shows the variance of log earnings calculated among employees of working age (between the ages of 25 and 59 inclusive). Employees are workers who report only salaried earnings in the entire observation period. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

education levels. Overall, the earnings dynamics of men and women appear similar. Notable differences emerge, however, when we zoom into education subgroups.

Starting with the permanent component, the variance of initial earnings, σ_α^2, is higher for men than for women. This suggests that men start with more diverse earnings levels, potentially due to sorting into a wider variety of industries or sectors relative to women. The variance in initial earnings appear to be similar for men regardless of their educational attainment, although for highly educated men, their initial earnings appear to be slightly more dispersed. Interestingly, women with a medium level of education have substantially more heterogeneity in their initial earnings compared to low- and high-educated women. There could be several reasons for this. Medium-educated women may be employed in a wider range of occupations, some of which offer more diverse pay structures. Additionally, women in this group are perhaps more likely to balance caregiving responsibilities alongside employment, potentially reflecting self-selection into part-time work or more flexible work arrangements.

As the variance of permanent shocks, σ_w^2, is higher for women than for men, this indicates that earning differentials have greater persistence among women. In fact, when considering the pooled point estimates, permanent shocks account for half of the variance of permanent earnings among mid-career men, compared to two-thirds for women.[28] Put simply, differences in earnings at the start of the career matter equally for men, while permanent earnings shocks are more relevant for women when we examine differences in long-run earnings. This is unsurprising as women generally face more variability in their career trajectories in the long-run, due to more frequent career interruptions that have long-term effects (e.g., caregiving and childbirth). Looking at education, the highly educated are more likely to face permanent earnings shocks, σ_w^2, compared to less educated peers. Generally, initial differences in earnings become less relevant later in the career for those with higher educational attainment, reflecting that there is greater mobility for these groups.

[28] This is calculated simply by the ratio, $\frac{\sigma_w^2}{\sigma_\alpha^2 + 15 \cdot \sigma_w^2}$. We take age 40 to be indicative of an individual in the middle of their career.

Table 1. Main parameter estimates by gender and education level

		Men				Women			
	All	Pooled	Low	Med	High	Pooled	Low	Med	High
Permanent component									
σ^2_α	0.075***	0.079***	0.062***	0.060***	0.072***	0.066***	0.038***	0.061***	0.034***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.005)	(0.004)	(0.002)
σ^2_w	0.008***	0.005***	—	0.002***	0.006***	0.009***	0.004***	0.005***	0.007***
	(0.0002)	(0.0002)	—	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0003)
Transitory component									
σ^2_{v1}	0.068***	0.069***	0.112***	0.080***	0.067***	0.066***	0.093***	0.075***	0.069***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)	(0.003)
ρ	0.392***	0.459***	0.775***	0.710***	0.472***	0.433***	0.738***	0.726***	0.538***
	(0.019)	(0.025)	(0.009)	(0.017)	(0.055)	(0.025)	(0.024)	(0.017)	(0.025)
θ	-0.151***	-0.226***	-0.469***	-0.410***	-0.228***	-0.182***	-0.423***	-0.401***	-0.261***
	(0.016)	(0.024)	(0.009)	(0.012)	(0.045)	(0.021)	(0.018)	(0.012)	(0.021)
σ^2_ϵ	0.061***	0.056***	0.076***	0.053***	0.054***	0.056***	0.75***	0.058***	0.055***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. For low-educated men, we omit a random walk and model their earnings to only follow an ARMA(1,1) process due to non-convergence. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

The autoregressive parameter, ρ, shows that transitory earnings shocks are quite persistent for both genders. Male earnings have a higher persistence, suggesting that temporary earnings shocks take longer to dissipate for men than for women over time. At the same time, the moving average parameter, θ, has a negative sign (indicating mean reversion) and is larger in absolute terms for men. Effectively, this means that even though transitory shocks take longer to completely dissipate for men, men's earnings recover more quickly than women's earnings in the immediate period following a shock.

There is also a clear education gradient in both genders; transitory shocks are more persistent for those with lower levels of education. The less educated have a higher variance in initial transitory shocks (σ^2_{v1}), indicating that they experience higher levels of earnings instability in general. This could be due to the nature of their employment (i.e., more variability in hours from part-time work or temporary contracts), but also due to their susceptibility to temporary unemployment shocks (OECD, 2020).

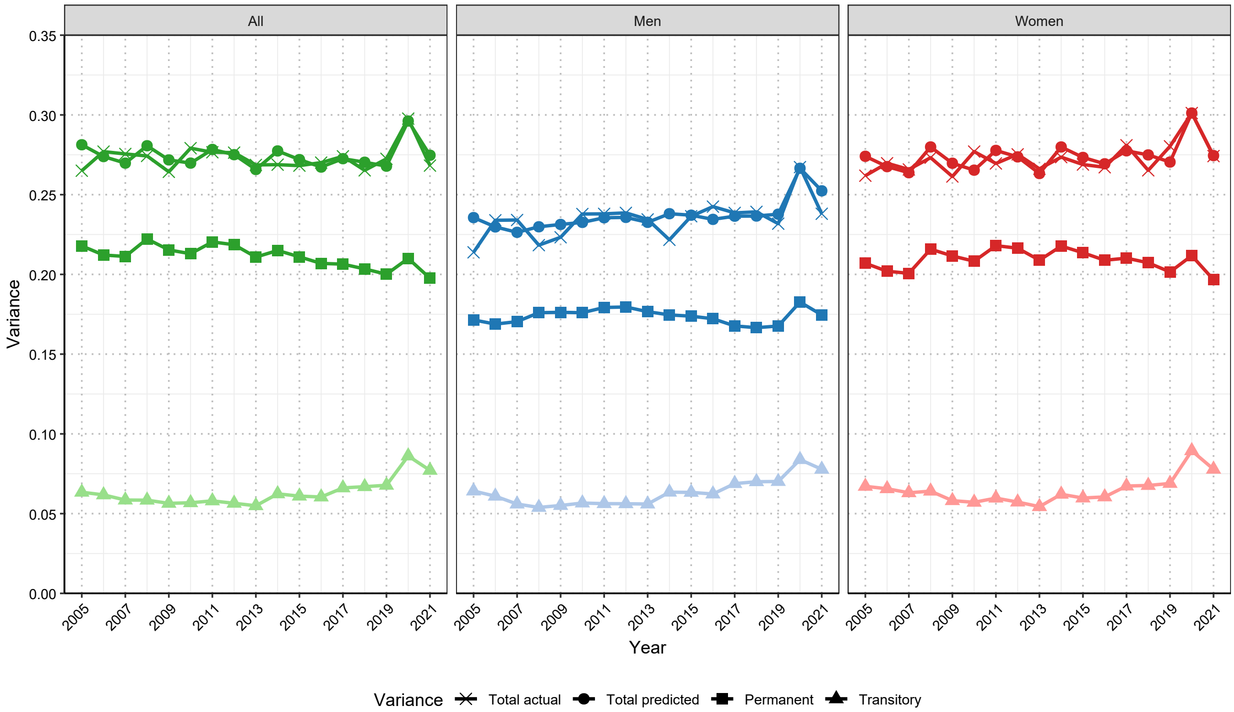
3.3 Trends in permanent inequality and earnings instability

Overall trends

We now compare the trends in the two drivers of inequality – permanent earnings inequality and earnings instability – for the general population, and for men and women. We decompose overall inequality into its drivers for mid-career individuals (i.e., age 40), abstracting from life-cycle effects. Each cross-section therefore reflects the dynamics of individuals who are in the middle of their career in that year. In Figure 6, we show how these dynamics evolve over time.

Generally, overall trends (i.e., "total predicted") follow the trends in inequality we observed previously (in Figure 3). That is, within-group inequality appears quite stable in the early 2000s, followed by an increase in inequality in more recent years. These trends apply to both men and women separately, although trends for women show some cyclicity. During the 2000s, both permanent inequality and earnings instability remained stable. From 2014 onwards, however, permanent inequality decreases while earnings instability is rising, reflecting the increasing volatility in earnings experienced by younger cohorts. The

Figure 6. Variance decomposition, mid-career worker by gender



Note: The figure shows the trends in earnings inequality decomposed into its permanent and transitory components, for mid-career employees.

decreasing trend aside, permanent inequality remains the main driver of overall (within-group) inequality throughout the years.

Trends by education subgroup

To determine if these dynamics differ by educational attainment, we disaggregate the population further by education and perform a similar variance decomposition for each subgroup. The top panel in Figure 7 shows the decompositions by education for men, and the bottom panel for women. Permanent inequality appears quite stable across both gender and education levels. The only exception is women with a low-level of education, where within-group permanent inequality has been decreasing since 2014.

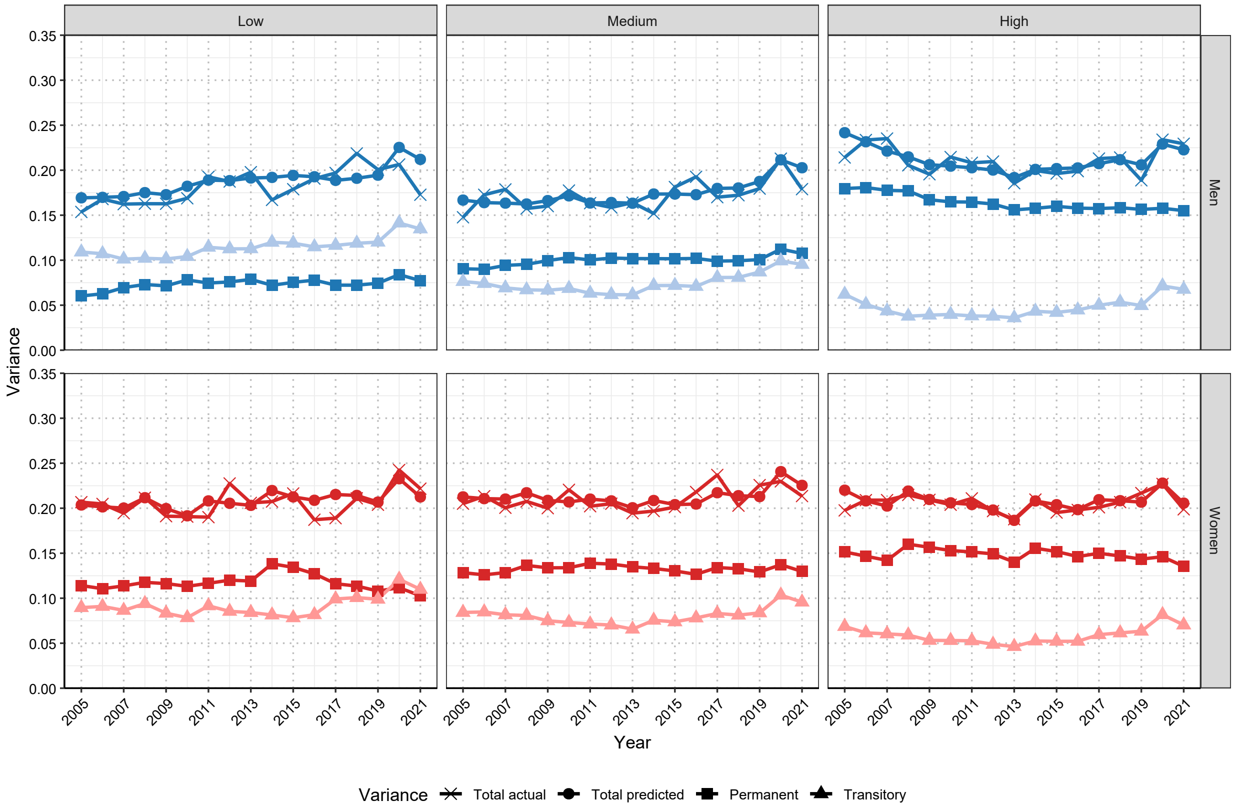
Across all subgroups, we also find a general increasing trend in earnings instability as seen in Figure 8. More striking, is the growing importance of earnings instability as a driver of inequality, particularly for the less educated. Here, we also see a clear relationship – the less educated have higher levels of earnings instability. For low-educated men, earnings instability is the main driver of within-group inequality. The relative contribution of earnings instability is also increasing among medium-educated individuals.

3.4 Decomposing permanent inequality

3.4.1 Subgroup contributions

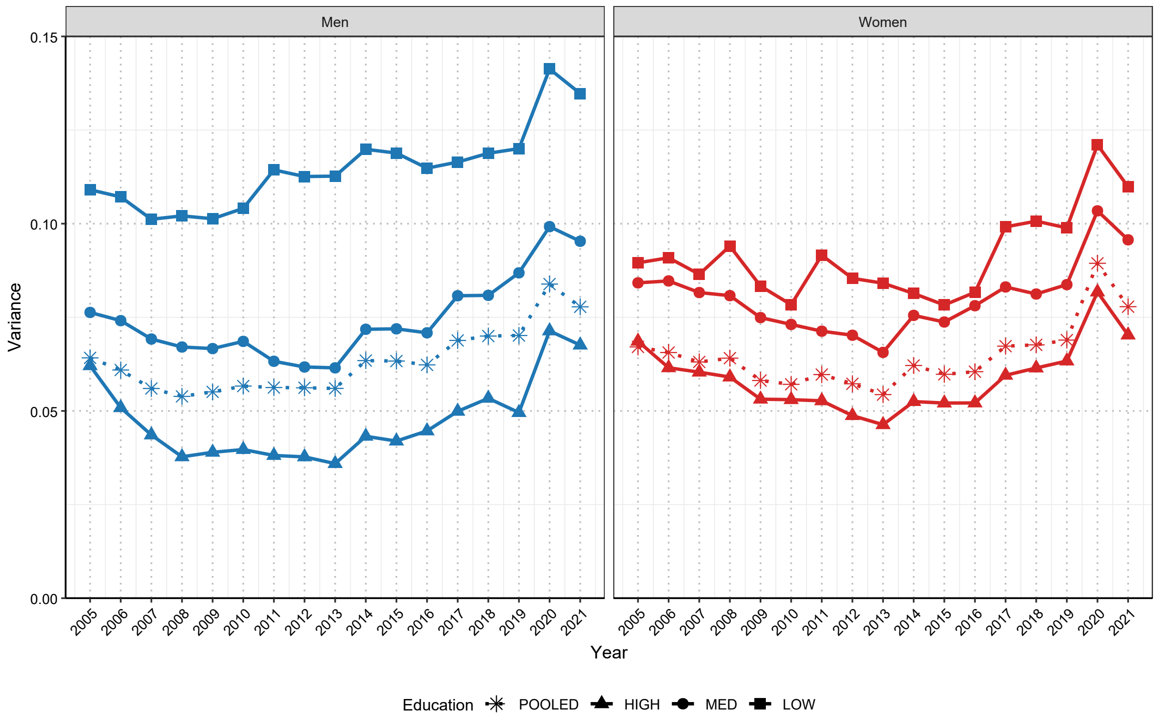
In the previous section, we show that permanent inequality has been relatively stable, and even decreasing in some subgroups. During this period, however, there have been major structural changes in the composition of the workforce, as tertiary education rates increased in younger cohorts, and especially among women. As such, assessing the relative contributions of different gender-education subgroups to overall inequality could reveal further insights behind underlying trends, in terms of changes to within-group and between-group inequality. In this section, we therefore adopt a similar approach taken by Sologon and

Figure 7. Variance decomposition, mid-career worker by gender



Note: The figure shows the trends in earnings inequality decomposed into its permanent and transitory components, for mid-career employees by gender and education subgroups. A transposed version of this figure is available in Figure C5 in Appendix C.

Figure 8. Earnings instability across gender and education levels



Note: Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

Van Kerm (2018) in assessing relative subgroup contributions to permanent inequality.

Using the additive properties of the variance, the permanent inequality of the entire working population, PV is equal to the sum of the permanent inequality within each subgroup, PV_g – weighted by their share, s_g – plus a residual term, B:

$$\begin{aligned} \mathrm{PV} &= \bar{\mathrm{PV}} + B \\ &= \sum_{g=1}^{k} s_g \cdot PV_g + B \end{aligned} \tag{3.1}$$

From the permanent inequality estimated for the entire working population, we recover B by subtracting the weighted sum of permanent inequality for k subgroups, $\bar{\mathrm{PV}}$. B can thus be interpreted as a "between-group" inequality term.[29] We apply this subgroup decomposition along the dimensions of gender and education. In Figures 9 and 10, we demonstrate these decompositions by graphing the overall permanent variance, PV, the permanent variance for each subgroup, $\mathrm{PV_g}$, the weighted sum of permanent variances across subgroups, $\bar{\mathrm{PV}}$, and the "between" component, B.

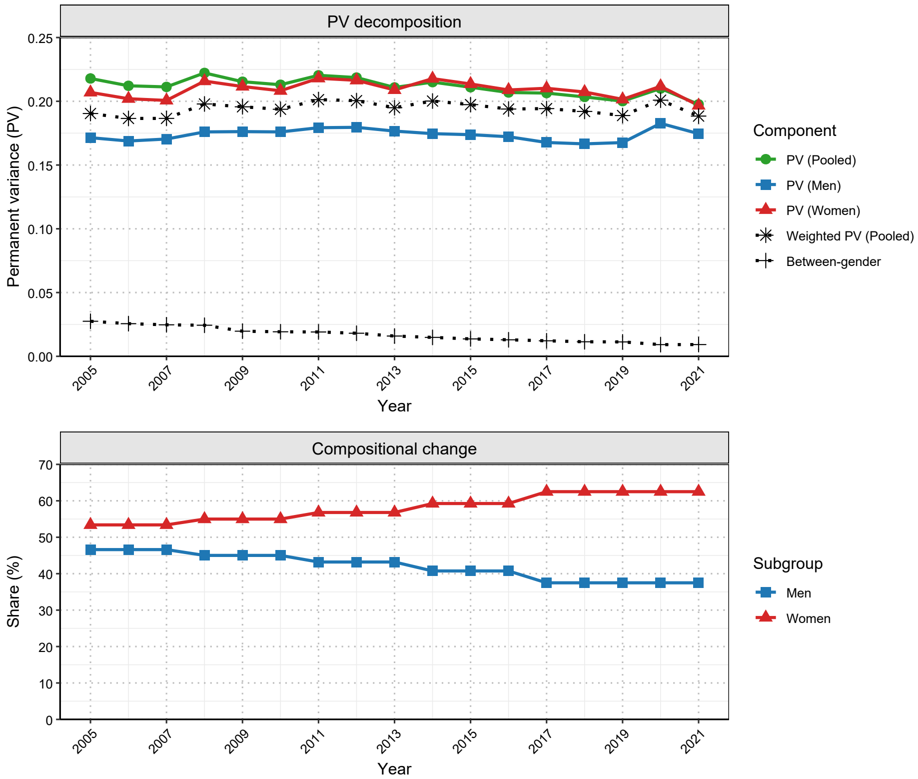
Figure 9 shows the decomposition by gender. We find that within-gender permanent inequality, $\bar{\mathrm{PV}}$, accounts for much of overall permanent inequality ("PV (Pooled)") among the working population, with inequality within women accounting for a higher share relative to men. Within-gender permanent inequality has been relatively stable, with a slight decline since 2014. This decline is relatively more pronounced among women. Given the increasing share of women in the workforce, total within-gender inequality declined. The declining trend in *overall* permanent inequality, however, is mostly driven by a decline in between-gender inequality. This corresponds with earlier studies which also find that the gender pay gap has been decreasing in Belgium (e.g., Capéau et al., 2024).

In Figure 10, we assess the relative contributions by education levels within each gender. Overall permanent inequality within both men and women is mainly accounted for by within-education inequality, $\bar{\mathrm{PV}}$. In terms of levels, women face larger within-education and between-education inequality compared to men. Between-education inequality declined slightly for both men and women. Much of overall within-education inequality among men is driven by the highly educated. On the contrary, the level of within-education inequality is more clustered for women across subgroups.

In terms of trends, there are notable differences across education levels. Permanent inequality has declined substantially among highly educated males, plateauing after 2013. Meanwhile, permanent inequality has increased slightly for low- and medium-educated males. Overall, within-group inequality for men has increased despite highly educated males accounting for an increasingly larger share in the workforce. High- and medium-educated women experienced a slight overall decrease in permanent inequality. For low-educated women, within-group inequality increased before 2014 and declined notably thereafter. Combining these trends, overall within-education inequality remained quite stable for women.

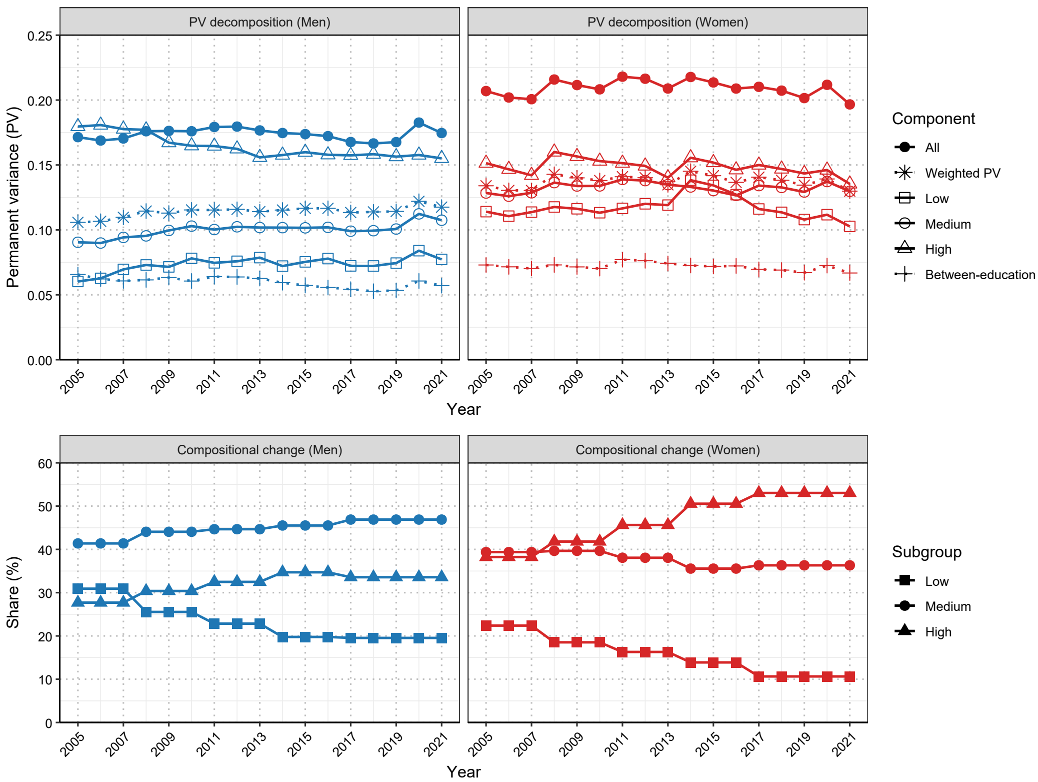
[29] Because we work with logarithms and demeaned earnings, the term B should not be taken as the conventional between-group inequality measure in classic decomposition literature.

Figure 9. Decomposition of permanent inequality by gender



Note: PV = permanent variance. Weighted PV = weighted sum of permanent variances across gender. Between-gender = residual between-gender permanent inequality.

Figure 10. Decomposition of permanent inequality by education levels



Note: All = within-gender permanent inequality. Weighted PV = weighted sum of permanent variances across education levels. Between-education = residual between-education permanent inequality. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to “Low”, “Medium” and “High” based on Eurostat conventions.

3.4.2 Factor contributions

If the above decompositions reflect simultaneous changes in the structure of the population, and in the within and between-group persistent inequality over time, next we seek to isolate the contribution of each factor in explaining the changes in permanent inequality over time. We apply the Biewen (2014) inequality decomposition approach, which assesses the *ceteris paribus* (i.e., direct) effect of each factor relative to a reference distribution (e.g., period 1). The change in permanent inequality, PV, between two periods can be written as:

$$\Delta \mathrm{PV}_{1-0} = \mathrm{PV}^1 - \mathrm{PV}^0 \tag{3.2}$$

This can be decomposed using a series of counterfactual PV^{1*} distributions that would prevail in period 1 if only factor k would change between period 1 and 0, and all other $m-k$ factors remain the same as in period 1.[30] The direct effect of factor k would be:

$$\mathrm{DX}_k = \mathrm{PV}^1 - \mathrm{PV}^{1*}_{\mathrm{k}^0} \tag{3.3}$$

The changes over time are decomposed into the sum of all direct effects for m factors, and a component that captures all possible interaction effects between the factors considered, $\sum$int:

$$\Delta \mathrm{PV}^{1-0} = \sum_{k=1}^{m} DX_k + \sum \mathrm{int} \tag{3.4}$$

We apply this to all factors that affect overall permanent inequality. Expanding Equation (3.1), overall permanent inequality can be constructed as:

$$\mathrm{PV} = s_m \cdot PV_m + s_f \cdot PV_f + B_{m,f} \tag{3.5}$$

$$\begin{aligned} &= s_m(s_{m,low} \cdot PV_{m,low} + s_{m,med} \cdot PV_{m,med} \\ &\quad + s_{m,high} \cdot PV_{m,high} + B_{m,edu}) \\ &\quad + s_f(s_{f,low} \cdot PV_{f,low} + s_{f,med} \cdot PV_{f,med} \\ &\quad + s_{f,high} \cdot PV_{f,high} + B_{f,edu}) \\ &\quad + B_{m,f} \end{aligned} \tag{3.6}$$

We calculate the direct effects of each factor in Equations (3.5) and (3.6), that is, the shares, s_g, within-group permanent inequality, PV_g, for each gender and gender-education subgroup, as well as the three between-group terms ($B_{m,f}$, $B_{m,edu}$ and $B_{f,edu}$). By construction, we cannot isolate changes in subgroup shares in a purely *ceteris paribus* way.[31] Therefore, we isolate total compositional changes in the educational structure *within* each gender from compositional changes in gender.[32]

As there are notable differences in trends across subperiods, we calculate the direct effects of the aforementioned factors for changes to PV in three sub-periods: $\Delta\mathrm{PV}^{2021-2013}$, $\Delta\mathrm{PV}^{2021-2005}$ and $\Delta\mathrm{PV}^{2013-2005}$. For comparability across sub-periods, we fix PV^{2021} as our reference distribution and calculate the direct effects in $\Delta\mathrm{PV}^{2013-2005}$ as the difference in direct effects between $\Delta\mathrm{PV}^{2021-2005}$ and $\Delta\mathrm{PV}^{2021-2013}$. Additionally, we assess the relative contribution, C_k, for each factor k, in all sub-periods using PV^{2021} as our reference:

$$C_k^{1-0} = \frac{\mathrm{DX}_k^{1-0}}{PV_{2021}} \cdot 100\% \tag{3.7}$$

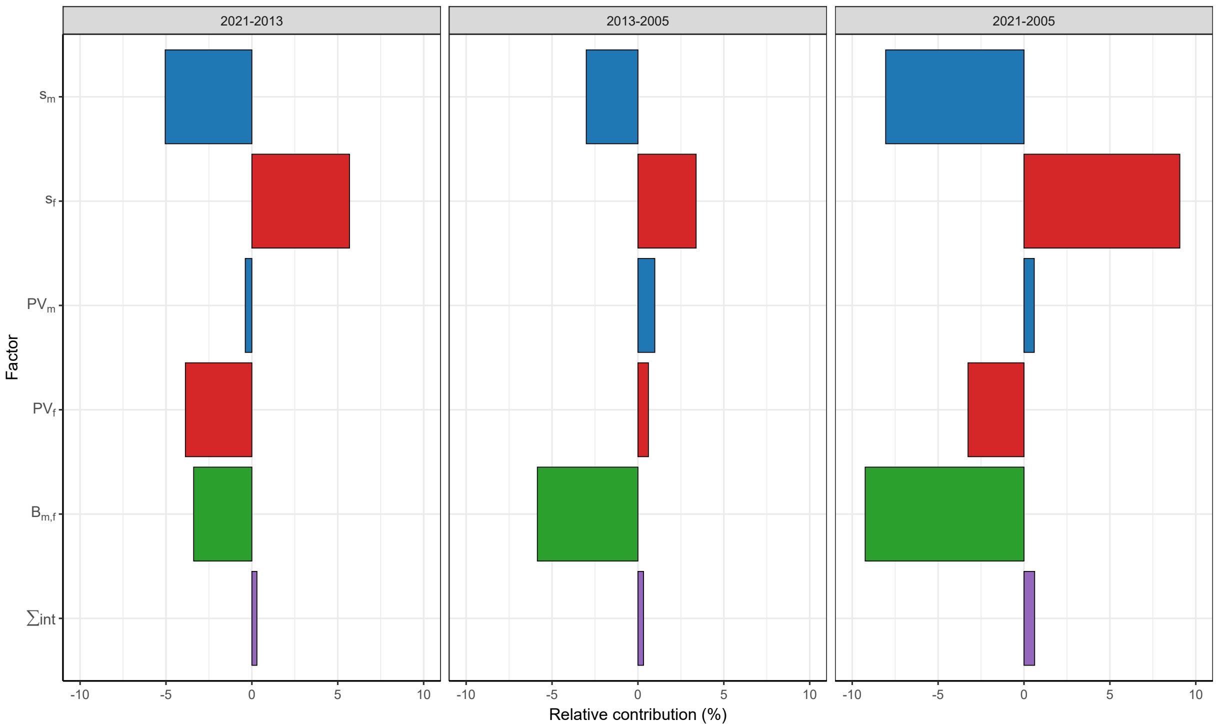
[30] The direct effect of a factor in Biewen (2014) is typically constructed as $PV^0 - PV^{0*}$, where the counterfactual distribution PV^{0*} uses k_1 for factor k and all other $m-k$ factors remain the same as in period 0. In other words, the counterfactual is usually interpreted as the distribution if only factor k *changes*, while we take the counterfactual as the distribution if only factor k *does not change*. We adopt this approach to have a fixed reference distribution to compare changes to permanent inequality across different subperiods.

[31] If we take s_{g_0} for a given subgroup but retain s_{g_1} for all other subgroups in the counterfactual distribution, then $\sum s_g \neq 1$.

[32] In essence, total changes in composition in education and in gender are thus *ceteris paribus*. In Appendix A.2, we provide more detail on how the direct effects of shares are calculated, as well as for all other factors.

We begin with applying this decomposition to Equation (3.5) below in Figure 11.

Figure 11. Decomposition of permanent inequality by factor (gender)



Note: The direct effect of each factor for each subperiod is calculated relative to permanent inequality in 2021. Subgroup shares are simultaneously changed.

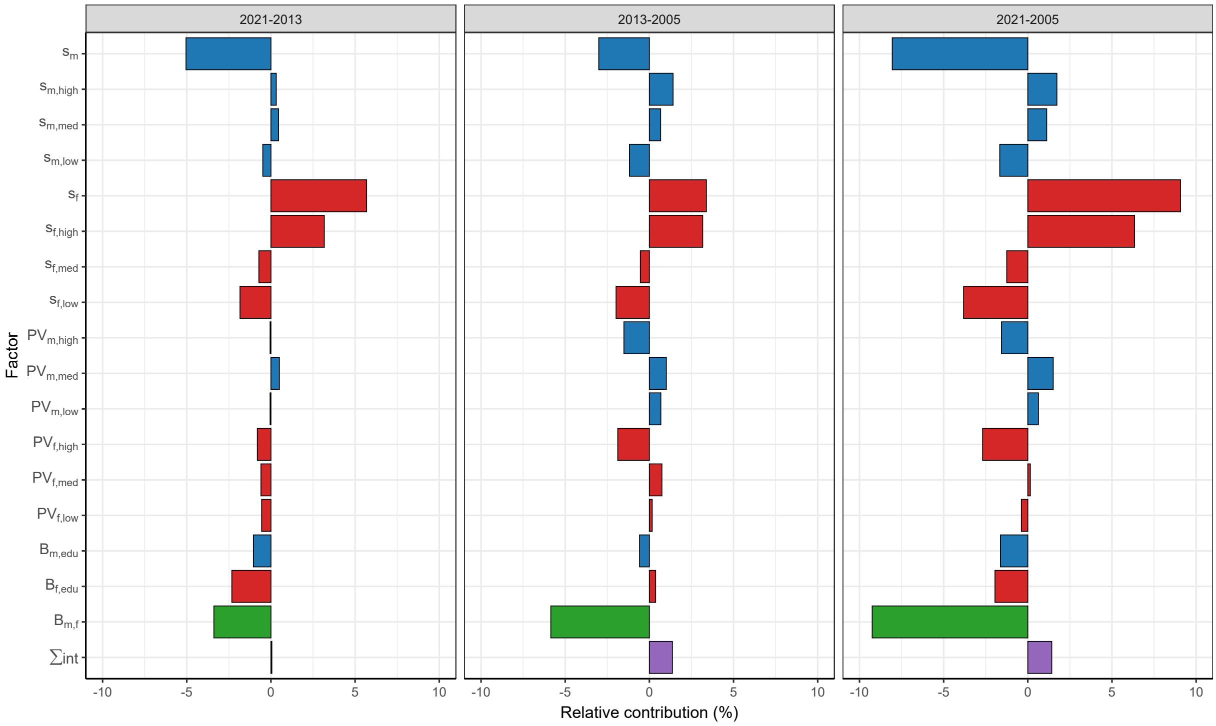
Recall that permanent inequality among the working population declined between 2005 and 2021, with most of the decrease occurring in the later period (2013–2021), while the earlier years (2005–2013) were marked by relative stability. Holding group shares constant, rising within-gender inequality had a disequalising effect in the initial sub-period. After 2013, within-gender inequality decreased. This decrease is notable among women and had a stronger equalising effect than the decrease in between-group inequality. Compositional shifts had a minimal net effect over the entire period. Much of the overall decline in permanent inequality can be attributed to a sustained decrease in between-gender inequality.

Next, we turn to a more granular decomposition of Equation (3.6), presented in Figure 12, which isolates changes in educational composition within each gender. In the earlier period, holding group composition fixed, rising within-education inequality among both low- and medium-educated subgroups had a disequalising effect while inequality within highly-educated subgroups decreased. In subsequent years, within-group inequality generally fell across all subgroups, with the exception of medium-educated men.

Holding within-group inequality and overall gender shares constant, increasing shares of medium- and highly-educated individuals among men and highly-educated individuals among women had a disequalising effect throughout. Meanwhile, inequality *between* education groups increased among women but decreased among men in earlier years. In subsequent years, between-education inequality decreased for both genders.

Ultimately, the disequalising effects of compositional shifts towards more educated subgroups are outweighed by the equalising contributions of falling within-group, between-education, and between-gender inequality, leading to an overall decrease in permanent inequality among the working population.

Figure 12. Decomposition of permanent inequality by factor (gender and education)



Note: The direct effect of each factor for each subperiod is calculated relative to permanent inequality in 2021. Subgroup shares are simultaneously changed.

3.5 Sensitivity to business cycles

Lastly, we determine whether business cycles have an influence on our estimates of permanent inequality and earnings instability by regressing these components on a linear time trend and GDP growth rates.[33] We do so for men and women separately, and subsequently by education subgroups within each gender.

Table 2 provides some evidence that permanent earnings inequality is procyclical. When GDP growth increases, there is a statistically significant decrease in permanent inequality for both men and women. There is however, no significant time trend in permanent inequality. This implies that in periods of economic expansion, the distribution of permanent earnings becomes more compressed, possibly because economic growth benefits a wider group of workers, reducing long-term disparities. Conversely, in downturns, permanent inequality widens, as earnings opportunities become more concentrated among higher earners or those with more secure employment. The absence of a significant time trend indicates that while persistent inequality fluctuates with the cycle, there is no evidence of a systematic long-term increase or decrease over the observed period.

Unlike permanent inequality, earnings instability does not appear to be sensitive to business cycles, suggesting that transitory shocks to earnings are not closely linked to cyclical fluctuations. This could reflect the influence of idiosyncratic shocks (e.g. job changes, temporary contracts, illness) which may be more persistent across business cycle phases. However, the significant positive time trend for both men and women points towards a systematic increase in earnings instability. This trend may be associated with structural labour market changes, such as the increase in flexible work arrangements, greater job turnover, or declining employment protection. The distinction between cyclical insensitivity and long-term growth highlights that instability is not primarily driven by short-run macroeconomic conditions, but by deeper transformations in labour markets and employment relationships.

[33] Other studies have done so similarly. For example, Baker and Solon (2003) perform a regression on unemployment rates, while Sologon and Van Kerm (2018) perform a regression on GDP growth rates. Beach et al. (2010) perform regressions with both unemployment rates and GDP growth rates.

Table 2. Business cycle sensitivity by gender

	Men		Women	
	Permanent	Transitory	Permanent	Transitory
Constant	0.1756***	0.0518***	0.2131***	0.0577***
	(0.0022)	(0.0032)	(0.0029)	(0.0041)
Time trend	-0.00004	0.0013***	-0.0002	0.0009**
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
GDP growth rate	-0.0011**	-0.0001	-0.0015**	-0.0005
	(0.0004)	(0.0006)	(0.0006)	(0.0008)
R^2	0.2821	0.5860	0.3340	0.2895

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: Regressions are estimated separately by gender with either long-run earnings inequality (permanent) or earnings instability (transitory) of midcareer workers as dependent variables. GDP growth rates are according to OECD data.

In Table 3, we perform separate regressions per gender-education subgroup. We find that permanent inequality is generally procyclical, with significance for low- and medium-educated men, and medium- and highly-educated women. Similar to our earlier estimations, there is no significant relationship between earnings instability and GDP growth.

We find statistically significant positive time trends for permanent inequality for low- and medium-educated men, but a decrease for highly-educated men. Only highly-educated women show a significant decrease in permanent inequality. We also find a statistically significant increase in earnings instability, particularly for men, larger in magnitude for less educated subgroups, indicating that structural shifts in the labour market disproportionately expose these groups to transitory earnings shocks. Only low-educated women show a significant increase in earnings instability, showing the vulnerability of this group to increasing short-term volatility in earnings.

Overall, taking business cycles into account, the time trends from both Tables 2 and 3 remain consistent with the trends discussed in Section 3.3. The point estimates for the constant also align with earlier conclusions regarding the relative contributions of permanent inequality and earnings instability to overall inequality within subgroups.

Table 3. Business cycle sensitivity by gender and education level

	Permanent			Transitory		
	Low	Medium	High	Low	Medium	High
Constant						
Men	0.0679***	0.0935***	0.1782***	0.0988***	0.0611***	0.0389***
	(0.0022)	(0.0017)	(0.0023)	(0.0033)	(0.0047)	(0.0056)
Women	0.1195***	0.1332***	0.1554***	0.0811***	0.0738***	0.0545***
	(0.0050)	(0.0020)	(0.0029)	(0.0054)	(0.0049)	(0.0049)
Time trend						
Men	0.0007***	0.0008***	-0.0016***	0.0018***	0.0015***	0.0009*
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0005)
Women	-0.0001	0.0001	-0.0006**	0.0013**	0.0007	0.0005
	(0.0005)	(0.0002)	(0.0003)	(0.0005)	(0.0005)	(0.0005)
GDP growth rate						
Men	-0.0008*	-0.0007*	0.0002	-0.0004	0.0002	0.0002
	(0.0004)	(0.0003)	(0.0005)	(0.0007)	(0.0009)	(0.0011)
Women	-0.0008	-0.0009**	-0.0011*	-0.0007	-0.0002	-0.0003
	(0.0010)	(0.0004)	(0.0006)	(0.0011)	(0.0010)	(0.0010)
R^2						
Men	0.5595	0.6984	0.8023	0.7217	0.4454	0.1857
Women	0.0461	0.2722	0.3664	0.3337	0.1577	0.0916

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: Regressions are estimated separately for men and women by education level (Low, Medium, High). Dependent variables are either long-run earnings inequality (permanent) or earnings instability (transitory). GDP growth rates are from OECD data.

4 Conclusion

In this paper, we set out to uncover what lies beneath the stable cross-sectional trends in inequality in Belgium by examining how permanent inequality and earnings instability among workers have evolved using rich administrative microdata from 2005 to 2021. By decomposing earnings dynamics by gender and education, our study offers the first detailed analysis of earnings in Belgium, revealing important changes in the labour market that aggregate inequality measures may conceal.

First, we find differences in both the variance of and persistence in permanent and transitory earnings across gender. In terms of gender, we find higher levels of permanent earnings inequality and persistence in permanent shocks among women compared to men, while men face higher levels of earnings instability and persistence in transitory earnings shocks. This contrasts with findings from other countries, where permanent inequality is generally found to be higher among men and earnings instability is higher among women (e.g., Beach et al. (2010) for Canada, Kässi (2014) for Finland, Gustafsson and Holmberg (2023) for Sweden). The distinct finding of higher persistent inequality for women in Belgium can be partly attributed to their higher rates of tertiary education relative to men, combined with a high prevalence of part-time work.

Second, a deeper analysis into education subgroups reveals important differences in their earnings dynamics, particularly for transitory earnings. Consistent with prior literature, we find in general that earnings instability is more pronounced, and more persistent, among the less educated while permanent earnings inequality is higher for more educated individuals. Additionally, we find that initial permanent earnings differences persist longer for those with lower educational attainment. Lastly, although our pooled results for gender suggest that men experience slightly higher earnings instability than women, this is largely driven by the high transitory variances of low-educated men. Differences in earnings instability across education levels are more clustered for women. Medium- and highly-educated women have more volatile earnings than men with similar levels of education. Therefore, apart from the low-educated, women generally exhibit greater earnings instability than men, consistent with the findings highlighted above.

Third, we observe a shift in the structure of inequality in Belgium towards earnings instability. Permanent inequality continues to be the main contributor to overall earnings inequality in Belgium, as found previously in Sologon and O'Donoghue (2009). We find that the declining trend in earnings instability documented by Sologon and O'Donoghue (2009) in the 1990s continued until 2013. Recent years, however, show a marked shift. Between 2013 and 2021, there has been a notable rise in earnings instability, particularly for low- and medium-educated groups and among men in general. Given that short-run macroeconomic conditions do not appear to be driving this growth, there may be important structural changes in the labour market – such as the growth of non-standard work, shifts in the distribution of skill and evolving gender roles – which warrant closer attention.

In contrast, permanent inequality has slightly declined, driven primarily by decreases in between-group inequality, namely between gender. Permanent inequality also appears to be procyclical, with higher sensitivity observed for less educated men, and conversely, higher sensitivity for higher educated women. While pooled gender models show no statistically significant time trends, we find significant increases in permanent inequality among less educated men, and decreases among both highly educated men and women. These results suggest that the increase in *overall* inequality between education subgroups found in Capéau et al. (2024) is not solely driven by increasing shares of highly educated workers, but also reflects the heterogeneity in earnings dynamics across education levels, particularly in transitory earnings.

Altogether, these developments call for policy responses aimed at mitigating temporary income shocks. Enhancing income-smoothing mechanisms, such as more responsive unemployment insurance, could provide better protection against short-term volatility. Expanding access to upskilling and retraining opportunities may also help lower-educated individuals move into more stable employment. Future research should explore the role of the tax-benefit system in cushioning instability. At the same time, the welfare implications of an increase in the transitory variance of earnings is not straightforward. Assessing these implications require modelling the decision to work and the endogeneity of labour supply. Due to data limitations (e.g., on data on hours worked), our paper is unable to touch on these normative implications. As better and richer data become increasingly available, it would be worthwhile to examine the drivers of rising earnings volatility among lower-skilled workers, including irregular hours and the prevalence of and preferences for non-standard work arrangements.

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A Calculations

A.1 Theoretical covariance structure and GMM estimation

In this appendix, we specify the theoretical moments and the estimation of parameters for an earnings process assumed to be the sum of a permanent component following a random walk, and a transitory component following an ARMA(1,1) process. Practically, we use the user-written Stata program **gmmcovearn** by Doris et al. (2011) to perform the estimation. However, we outlay how the estimation procedure is carried out here.

The theoretical variance-covariance matrix for cohort c has diagonal elements:

$$\sigma_{c1}^2 = \{q_c^2 p_1^2(\sigma_\alpha^2 + \sigma_w^2 X_{c1})\} + \left(s_c^2 \lambda_1^2 \sigma_{\nu 1}^2\right) \tag{A.1}$$

$$\begin{aligned}\sigma_{ct}^2 = &\{q_c^2 p_t^2(\sigma_\alpha^2 + \sigma_w^2 X_{ct})\} \\ &+ \{s_c^2 \lambda_t^2(\rho^{2t-2}\sigma_{\nu 1}^2 + K\sum_{w=0}^{t-2}\rho^{2w})\}, \quad t > 1,\end{aligned} \tag{A.2}$$

And off-diagonal elements:

$$\begin{aligned}\mathrm{Cov}(y_{ct}, y_{c(t+s)}) = &\, q_c^2 p_t p_{t+s}\sigma_\alpha^2 \\ &+ s_c^2 \lambda_t \lambda_{t+s}\left(\rho^s \sigma_{\nu 1}^2 + \rho^{s-1}\theta\sigma_\epsilon^2\right), \quad t = 1 \text{ and } s > 0,\end{aligned} \tag{A.3}$$

$$\begin{aligned}\mathrm{Cov}(y_{ct}, y_{c(t+s)}) = &\, q_c^2 p_t p_{t+s}\sigma_\alpha^2 \\ &+ s_c^2 \lambda_t \lambda_{t+s}\left(\rho^{2t+s-2}\sigma_{\nu 1}^2 + \rho^s K \sum_{w=0}^{t-2}\rho^{2w} + \rho^{s-1}\theta\sigma_\epsilon^2\right), \\ & t > 1 \text{ and } s > 0.\end{aligned} \tag{A.4}$$

where s is the number of leads or lags from year t, X_{ct} is the average experience of cohort c in period t, and $K = \sigma_\epsilon^2(1 + \theta^2 + 2\rho\theta)$. The theoretical variance-covariance matrix for cohort c is

$$\mathbf{M}_c(\phi) = \begin{bmatrix} \sigma_{c1}^2 & \mathrm{Cov}(y_{c1}, y_{c2}) & \mathrm{Cov}(y_{c1}, y_{c3}) & \cdots & \mathrm{Cov}(y_{c1}, y_{cT}) \\ \mathrm{Cov}(y_{c2}, y_{c1}) & \sigma_{c2}^2 & \mathrm{Cov}(y_{c2}, y_{c3}) & \cdots & \mathrm{Cov}(y_{c2}, y_{cT}) \\ \mathrm{Cov}(y_{c3}, y_{c1}) & \mathrm{Cov}(y_{c3}, y_{c2}) & \sigma_{c3}^2 & \cdots & \mathrm{Cov}(y_{c3}, y_{cT}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{Cov}(y_{cT}, y_{c1}) & \mathrm{Cov}(y_{cT}, y_{c2}) & \mathrm{Cov}(y_{cT}, y_{c3}) & \cdots & \sigma_{cT}^2 \end{bmatrix},$$

and where the vector, ϕ, includes the following parameters to be estimated:

$$\phi = \left(\{q_c\}_{c=1}^C, \{p_T\}_{t=1}^T, \{s_c\}_{c=1}^C, \{\lambda_t\}_{t=1}^T, \sigma_\alpha^2, \sigma_w^2, \sigma_{\nu 1}^2, \sigma_\epsilon^2, \rho, \theta\right).$$

The half-vectorised matrices for all cohorts are then stacked:

$$\mathbf{M}(\phi) = \begin{bmatrix} \mathrm{vech}(\mathbf{M}_1(\phi)) \\ \mathrm{vech}(\mathbf{M}_2(\phi)) \\ \vdots \\ \mathrm{vech}(\mathbf{M}_C(\phi)) \end{bmatrix}$$

Subsequently, the corresponding vectors of cohort-specific sample moments calculated from the data are also stacked into $\hat{\mathbf{M}}$ and matched with the stacked vector of theoretical moments, $\mathbf{M}(\phi)$, resulting in a vector of moment conditions:

$$\mathbb{E}[g(\phi)] = \mathbb{E}[\hat{\mathbf{M}} - \mathbf{M}(\phi)] \tag{A.5}$$

At the true parameter values ϕ_0, the expectation of residuals is equal to zero, i.e., $\mathbb{E}[g(\phi)] = \mathbf{0}$. The equally weighted minimum distance (EWMD) estimator $\hat{\Phi}$ thus finds the vector of parameters ϕ that minimises the objective function, $Q(\phi)$:

$$\hat{\Phi} = \arg\min_{\phi} Q(\phi) \tag{A.6}$$

where

$$\begin{aligned} Q(\phi) &= g(\phi)'\mathbf{W}g(\phi) \\ &= [\hat{\mathbf{M}} - \mathbf{M}(\phi)]'\mathbf{W}[\hat{\mathbf{M}} - \mathbf{M}(\phi)] \end{aligned} \tag{A.7}$$

and $\mathbf{W}$ is a weighting matrix, which in this case refers to an identity matrix. All moment conditions in (A.5) are thus assigned equal weight. Altonji and Segal (1996) show that the use of the identity matrix is robust in finite samples.

A.2 Biewen decomposition: calculation of direct effects

In Section 3.4.1, we apply the Biewen (2014) decomposition to assess the relative contributions of factors to permanent inequality. In particular, we calculate the direct effects of k factors where:

$$k \in \left\{ \begin{array}{lll} s_{m,\text{low}} & s_{m,\text{med}} & s_{m,\text{high}} \\ s_{f,\text{low}} & s_{f,\text{med}} & s_{f,\text{high}} \\ PV_{m,\text{low}} & PV_{m,\text{med}} & PV_{m,\text{high}} \\ PV_{f,\text{low}} & PV_{f,\text{med}} & PV_{f,\text{high}} \\ B_{m,\text{edu}} & B_{f,\text{edu}} & B_{m,f} \end{array} \right\} \tag{A.8}$$

After simplification, the direct effects of the between terms can be calculated as:

$$\text{DFX}_{B_{m,f}} = B^1_{m,f} - B^0_{m,f} \tag{A.9}$$

$$\text{DFX}_{B_{x,\text{edu}}} = s^1_x \left(\text{B}^1_{x,\text{edu}} - \text{B}^0_{x,\text{edu}}\right), \qquad x \in \{m, f\} \tag{A.10}$$

The direct effects of within-group inequality, $PV_{x,edu}$, for each gender-education subgroup can be calculated as:

$$\text{DFX}_{PV_{x,edu}} = s^1_x s^1_{x,edu}(PV^1_{x,edu} - PV^0_{x,edu}), \quad x \in \{m, f\} \quad \text{edu} \in \{low, med, high\} \tag{A.11}$$

Calculating the direct effects of shares, however, is not as straightforward as the factors above. The difficulty with assessing compositional changes, and thus shares, is that using the observed share of subgroup g in period 1 necessarily implies a simultaneous change in shares for all other subgroups. If we directly use the observed share of subgroup g in period 1, and retain all other subgroup shares as their observed shares at period 0, then $\sum_g s_g \neq 1$.

As such, we assess the *ceteris paribus* effects of changing educational shares *within* each gender, holding overall gender shares constant,

$$DFX_{\text{s}_{\text{edu}}} = \sum_{\substack{x \in \{m,f\} \\ g \in \text{edu}}} s^1_x (s^1_{x,g} - s^0_{x,g})\text{PV}^0_{x,g} \tag{A.12}$$

and the *ceteris paribus* effects of changing gender shares, while holding educational shares within each gender constant:

$$DFX_{\mathrm{s_x}} = \sum_{x}(s_x^1 - s_x^0)[\sum_{g\in\mathrm{edu}}(s_{x,g}^1 \mathrm{PV}_{x,g}^1) + B_{x,g}^1] \tag{A.13}$$

The contribution of each gender-education subgroup to $DFX_{\mathrm{s_{edu}}}$, and each gender to $DFX_{\mathrm{s_x}}$ is then graphed.

B Supplementary tables

Table B1. Sample size by cohort, gender, and age

Cohort	Birth Year	$\overline{\text{Age}}_{2005}$	$\overline{\text{Age}}_{2021}$	N	
				Men	Women
C_1	1962-1964	42	58	14,268	15,279
C_2	1965-1967	39	55	13,726	15,724
C_3	1968-1970	36	52	13,009	15,891
C_4	1971-1973	33	49	12,647	16,626
C_5	1974-1976	30	46	11,731	17,061
C_6	1977-1980	26.5	43.5	16,053	26,763
Total				81,434	107,343

Note: The sample is a 10% simple random sample of tax-filers from administrative tax return data. The sample is restricted to the working age population (ages 25 to 59 inclusive) and to employees – workers who only reported salaried earnings in the entire observation period.

Table B2. Sample size by cohort, gender and education level

Cohort	Men			Women		
	Low	Medium	High	Low	Medium	High
C_1	5,246	5,235	3,787	4,243	5,543	5,493
C_2	4,244	5,680	3,802	3,521	6,191	6,012
C_3	3,323	5,733	3,953	2,944	6,303	6,644
C_4	2,889	5,649	4,109	2,710	6,329	7,587
C_5	2,319	5,340	4,072	2,368	6,067	8,625
C_6	3,137	7,527	5,389	2,848	9,720	14,195
Total	21,158	35,164	25,112	18,634	40,153	48,556

Note: Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to “Low”, “Medium” and “High” based on Eurostat conventions.

Table B3. Time-specific permanent shifters by gender

	All	Men	Women
p_{2006}	0.987***	0.992***	0.988***
	(0.002)	(0.004)	(0.004)
p_{2007}	0.985***	0.997***	0.985***
	(0.003)	(0.005)	(0.004)
p_{2008}	0.977***	0.993***	0.979***
	(0.003)	(0.005)	(0.005)
p_{2009}	0.962***	0.994***	0.970***
	(0.004)	(0.006)	(0.005)
p_{2010}	0.956***	0.993***	0.962***
	(0.004)	(0.006)	(0.006)
p_{2011}	0.948***	0.982***	0.960***
	(0.004)	(0.007)	(0.006)
p_{2012}	0.944***	0.983***	0.956***
	(0.004)	(0.008)	(0.006)
p_{2013}	0.927***	0.975***	0.940***
	(0.004)	(0.008)	(0.007)
p_{2014}	0.920***	0.967***	0.933***
	(0.005)	(0.008)	(0.007)
p_{2015}	0.911***	0.965***	0.924***
	(0.005)	(0.009)	(0.007)
p_{2016}	0.902***	0.960***	0.914***
	(0.005)	(0.009)	(0.007)
p_{2017}	0.906***	0.977***	0.911***
	(0.005)	(0.010)	(0.007)
p_{2018}	0.899***	0.973***	0.904***
	(0.005)	(0.010)	(0.008)
p_{2019}	0.892***	0.976***	0.892***
	(0.005)	(0.010)	(0.008)
p_{2020}	0.913***	1.019***	0.914***
	(0.006)	(0.011)	(0.008)
p_{2021}	0.886***	0.997***	0.881***
	(0.006)	(0.011)	(0.008)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. p_{2005} is normalised to 1.

Table B4. Time-specific permanent shifters by gender and education

	Men			Women		
	Low	Med	High	Low	Med	High
p_{2006}	1.020***	0.997***	1.003***	0.985***	0.990***	0.984***
	(0.013)	(0.008)	(0.008)	(0.014)	(0.008)	(0.008)
p_{2007}	1.075***	1.021***	0.994***	0.998***	1.001***	0.969***
	(0.016)	(0.011)	(0.009)	(0.017)	(0.009)	(0.009)
p_{2008}	1.088***	1.021***	1.009***	1.005***	1.007***	0.961***
	(0.016)	(0.013)	(0.010)	(0.020)	(0.011)	(0.010)
p_{2009}	1.077***	1.043***	0.980***	0.999***	0.997***	0.950***
	(0.018)	(0.017)	(0.011)	(0.022)	(0.012)	(0.010)
p_{2010}	1.125***	1.060***	0.973***	0.986***	0.997***	0.939***
	(0.020)	(0.019)	(0.012)	(0.024)	(0.013)	(0.010)
p_{2011}	1.116***	1.063***	0.969***	0.974***	0.998***	0.929***
	(0.021)	(0.022)	(0.013)	(0.025)	(0.014)	(0.010)
p_{2012}	1.125***	1.075***	0.963***	0.988***	0.995***	0.923***
	(0.022)	(0.025)	(0.014)	(0.027)	(0.015)	(0.010)
p_{2013}	1.145***	1.072***	0.943***	0.984***	0.984***	0.894***
	(0.024)	(0.027)	(0.015)	(0.028)	(0.016)	(0.010)
p_{2014}	1.149***	1.065***	0.939***	0.977***	0.974***	0.896***
	(0.025)	(0.028)	(0.016)	(0.029)	(0.016)	(0.010)
p_{2015}	1.174***	1.064***	0.946***	0.962***	0.964***	0.885***
	(0.025)	(0.030)	(0.016)	(0.030)	(0.017)	(0.010)
p_{2016}	1.194***	1.066***	0.940***	0.936***	0.950***	0.868***
	(0.026)	(0.032)	(0.017)	(0.031)	(0.017)	(0.010)
p_{2017}	1.221***	1.071***	0.966***	0.928***	0.946***	0.869***
	(0.026)	(0.033)	(0.018)	(0.031)	(0.018)	(0.011)
p_{2018}	1.221***	1.073***	0.969***	0.917***	0.941***	0.860***
	(0.026)	(0.035)	(0.018)	(0.032)	(0.019)	(0.011)
p_{2019}	1.240***	1.080***	0.963***	0.895***	0.928***	0.850***
	(0.027)	(0.036)	(0.019)	(0.033)	(0.019)	(0.011)
p_{2020}	1.317***	1.141***	0.967***	0.910***	0.957***	0.858***
	(0.030)	(0.039)	(0.019)	(0.034)	(0.020)	(0.011)
p_{2021}	1.263***	1.116***	0.959***	0.873***	0.930***	0.826***
	(0.028)	(0.039)	(0.019)	(0.033)	(0.020)	(0.011)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. For low-educated men, we omit a random walk and model their earnings to only follow an ARMA(1,1) process. p_{2005} is normalised to 1. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

Table B5. Time-specific transitory shifters by gender

	All	Men	Women
l_{2006}	1.005***	1.028***	1.025***
	(0.015)	(0.016)	(0.020)
l_{2007}	0.982***	0.997***	1.012***
	(0.016)	(0.018)	(0.022)
l_{2008}	0.959***	0.963***	0.992***
	(0.015)	(0.017)	(0.020)
l_{2009}	0.942***	0.974***	0.945***
	(0.014)	(0.017)	(0.019)
l_{2010}	0.946***	0.988***	0.936***
	(0.014)	(0.017)	(0.018)
l_{2011}	0.928***	0.951***	0.921***
	(0.014)	(0.016)	(0.018)
l_{2012}	0.916***	0.951***	0.902***
	(0.014)	(0.016)	(0.018)
l_{2013}	0.903***	0.949***	0.879***
	(0.014)	(0.017)	(0.018)
l_{2014}	0.920***	0.972***	0.890***
	(0.014)	(0.017)	(0.018)
l_{2015}	0.909***	0.971***	0.873***
	(0.014)	(0.017)	(0.018)
l_{2016}	0.905***	0.964***	0.878***
	(0.014)	(0.017)	(0.019)
l_{2017}	0.894***	0.950***	0.874***
	(0.014)	(0.017)	(0.019)
l_{2018}	0.900***	0.958***	0.877***
	(0.014)	(0.017)	(0.019)
l_{2019}	0.905***	0.959***	0.885***
	(0.015)	(0.018)	(0.019)
l_{2020}	1.021***	1.049***	1.008***
	(0.016)	(0.020)	(0.022)
l_{2021}	0.966***	1.010***	0.940***
	(0.016)	(0.020)	(0.022)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. l_{2005} is normalised to 1.

Table B6. Time-specific transitory shifters by gender and education

	Men			Women		
	Low	Med	High	Low	Med	High
l_{2006}	1.026***	1.046***	0.957***	1.013***	1.014***	0.990***
	(0.013)	(0.015)	(0.032)	(0.021)	(0.015)	(0.024)
l_{2007}	1.019***	1.044***	0.897***	0.990***	1.002***	0.994***
	(0.017)	(0.019)	(0.035)	(0.026)	(0.019)	(0.028)
l_{2008}	1.011***	1.027***	0.829***	0.974***	0.976***	0.969***
	(0.019)	(0.020)	(0.032)	(0.027)	(0.021)	(0.026)
l_{2009}	1.016***	1.033***	0.843***	0.918***	0.942***	0.920***
	(0.020)	(0.020)	(0.031)	(0.025)	(0.018)	(0.024)
l_{2010}	1.035***	1.052***	0.851***	0.891***	0.931***	0.920***
	(0.020)	(0.020)	(0.031)	(0.024)	(0.018)	(0.024)
l_{2011}	1.009***	0.996***	0.826***	0.915***	0.907***	0.893***
	(0.020)	(0.019)	(0.030)	(0.024)	(0.017)	(0.023)
l_{2012}	1.003***	0.985***	0.822***	0.884***	0.900***	0.859***
	(0.020)	(0.019)	(0.031)	(0.023)	(0.017)	(0.023)
l_{2013}	1.004***	0.984***	0.802***	0.877***	0.871***	0.837***
	(0.019)	(0.019)	(0.031)	(0.023)	(0.017)	(0.023)
l_{2014}	0.998***	1.011***	0.848***	0.858***	0.884***	0.854***
	(0.019)	(0.020)	(0.033)	(0.024)	(0.017)	(0.024)
l_{2015}	0.995***	1.012***	0.836***	0.842***	0.874***	0.851***
	(0.019)	(0.020)	(0.032)	(0.024)	(0.018)	(0.024)
l_{2016}	0.978***	1.005***	0.862***	0.860***	0.899***	0.851***
	(0.019)	(0.020)	(0.033)	(0.025)	(0.018)	(0.024)
l_{2017}	0.973***	1.011***	0.828***	0.860***	0.884***	0.863***
	(0.019)	(0.020)	(0.033)	(0.025)	(0.019)	(0.025)
l_{2018}	0.983***	1.011***	0.856***	0.867***	0.874***	0.877***
	(0.020)	(0.021)	(0.034)	(0.026)	(0.019)	(0.026)
l_{2019}	0.988***	1.048***	0.825***	0.859***	0.887***	0.890***
	(0.020)	(0.022)	(0.033)	(0.027)	(0.020)	(0.026)
l_{2020}	1.072***	1.120***	0.990***	0.951***	0.986***	1.011***
	(0.022)	(0.024)	(0.039)	(0.030)	(0.022)	(0.029)
l_{2021}	1.047***	1.098***	0.963***	0.906***	0.949***	0.938***
	(0.023)	(0.023)	(0.040)	(0.031)	(0.023)	(0.029)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. For low-educated men, we omit a random walk and model their earnings to only follow an ARMA(1,1) process. l_{2005} is normalised to 1. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

Table B7. Cohort-specific shifters by gender

	All	Men	Women
Permanent component			
$q_{65\text{-}67}$	1.039***	1.033***	1.033***
	(0.008)	(0.012)	(0.010)
$q_{68\text{-}70}$	1.074***	1.054***	1.077***
	(0.009)	(0.012)	(0.011)
$q_{71\text{-}73}$	1.102***	1.076***	1.104***
	(0.009)	(0.013)	(0.012)
$q_{74\text{-}76}$	1.122***	1.079***	1.135***
	(0.010)	(0.014)	(0.013)
$q_{77\text{-}80}$	1.116***	1.046***	1.143***
	(0.010)	(0.015)	(0.014)
Transitory component			
$s_{65\text{-}67}$	0.969***	0.965***	1.010***
	(0.012)	(0.014)	(0.018)
$s_{68\text{-}70}$	0.991***	0.983***	1.040***
	(0.012)	(0.014)	(0.019)
$s_{71\text{-}73}$	1.021***	1.018***	1.081***
	(0.012)	(0.014)	(0.018)
$s_{74\text{-}76}$	1.068***	1.058***	1.142***
	(0.012)	(0.014)	(0.019)
$s_{77\text{-}80}$	1.131***	1.127***	1.210***
	(0.011)	(0.013)	(0.018)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. For low-educated men, we omit a random walk and model their earnings to only follow an ARMA(1,1) process. $q_{62\text{-}64}$ and $s_{62\text{-}64}$ are normalised to 1.

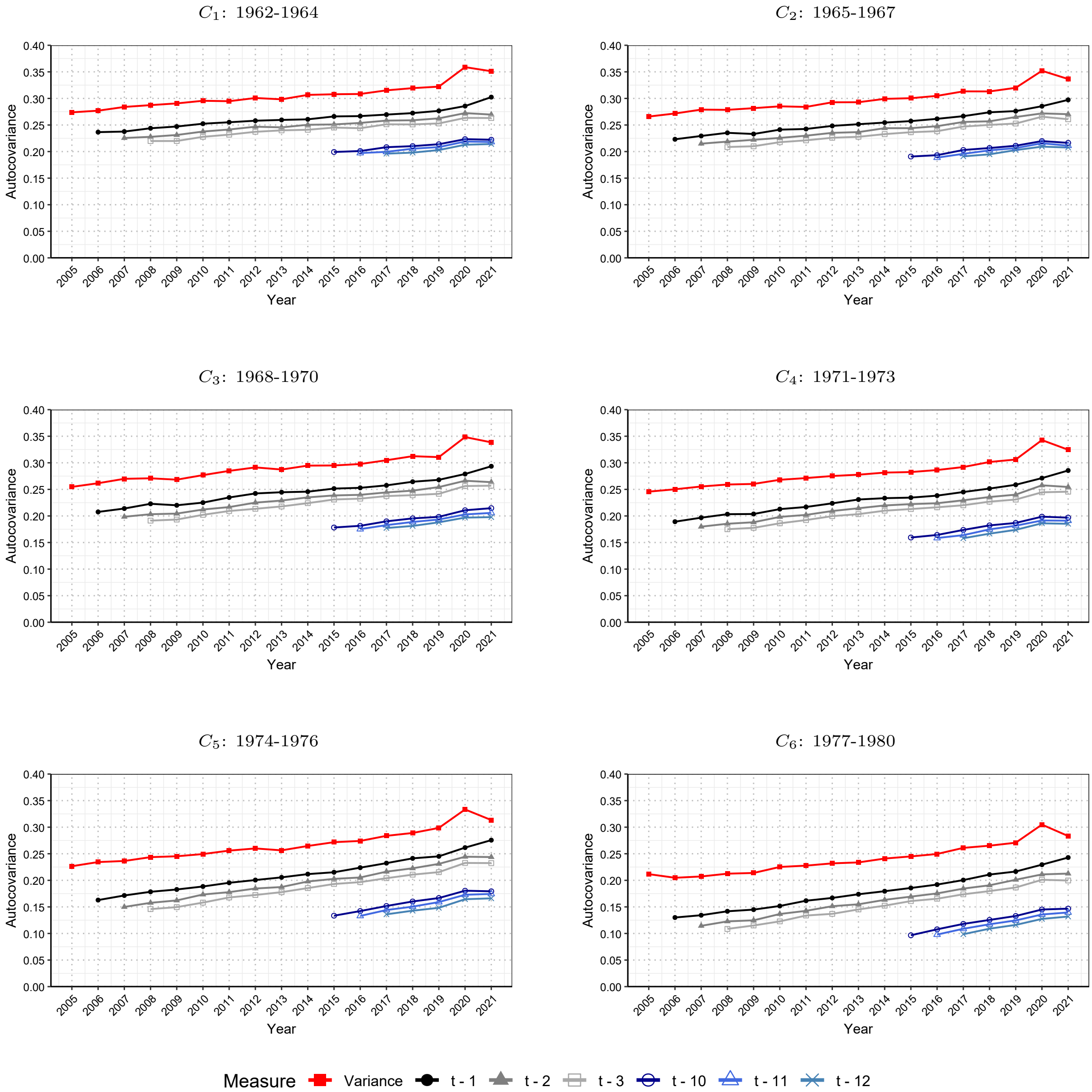
Table B8. Cohort-specific shifters by gender and education

	Men			Women		
	Low	Med	High	Low	Med	High
Permanent component						
$q_{65\text{-}67}$	0.986***	1.002***	1.072***	1.066***	0.985***	1.050***
	(0.025)	(0.019)	(0.023)	(0.028)	(0.017)	(0.021)
$q_{68\text{-}70}$	0.998***	1.008***	1.055***	1.077***	1.008***	1.124***
	(0.028)	(0.021)	(0.022)	(0.032)	(0.019)	(0.023)
$q_{71\text{-}73}$	0.984***	0.992***	1.058***	1.107***	1.026***	1.130***
	(0.028)	(0.023)	(0.023)	(0.039)	(0.021)	(0.023)
$q_{74\text{-}76}$	0.939***	0.998***	1.069***	1.202***	1.029***	1.189***
	(0.031)	(0.030)	(0.025)	(0.047)	(0.024)	(0.026)
$q_{77\text{-}80}$	0.884***	0.979***	1.038***	1.159***	1.064***	1.203***
	(0.024)	(0.034)	(0.028)	(0.054)	(0.028)	(0.027)
Transitory component						
$s_{65\text{-}67}$	0.985***	0.974***	0.964***	0.980***	1.062***	0.997***
	(0.015)	(0.018)	(0.032)	(0.026)	(0.024)	(0.028)
$s_{68\text{-}70}$	1.011***	0.993***	0.974***	1.040***	1.088***	1.015***
	(0.016)	(0.018)	(0.031)	(0.028)	(0.024)	(0.029)
$s_{71\text{-}73}$	1.091***	1.009***	0.982***	1.095***	1.103***	1.042***
	(0.017)	(0.018)	(0.031)	(0.030)	(0.025)	(0.027)
$s_{74\text{-}76}$	1.132***	1.062***	1.019***	1.101***	1.166***	1.088***
	(0.019)	(0.019)	(0.031)	(0.032)	(0.025)	(0.028)
$s_{77\text{-}80}$	1.146***	1.127***	1.122***	1.212***	1.223***	1.146***
	(0.017)	(0.018)	(0.030)	(0.028)	(0.024)	(0.026)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Note: The earnings dynamics for each group are estimated separately. The earnings of all groups are modelled with a random walk in the permanent component, and an ARMA(1,1) transitory process. For low-educated men, we omit a random walk and model their earnings to only follow an ARMA(1,1) process. $q_{62\text{-}64}$ and $s_{62\text{-}64}$ are normalised to 1. Education is based on the highest education level achieved according to the census data in 2021. We group the ISCED education levels to "Low", "Medium" and "High" based on Eurostat conventions.

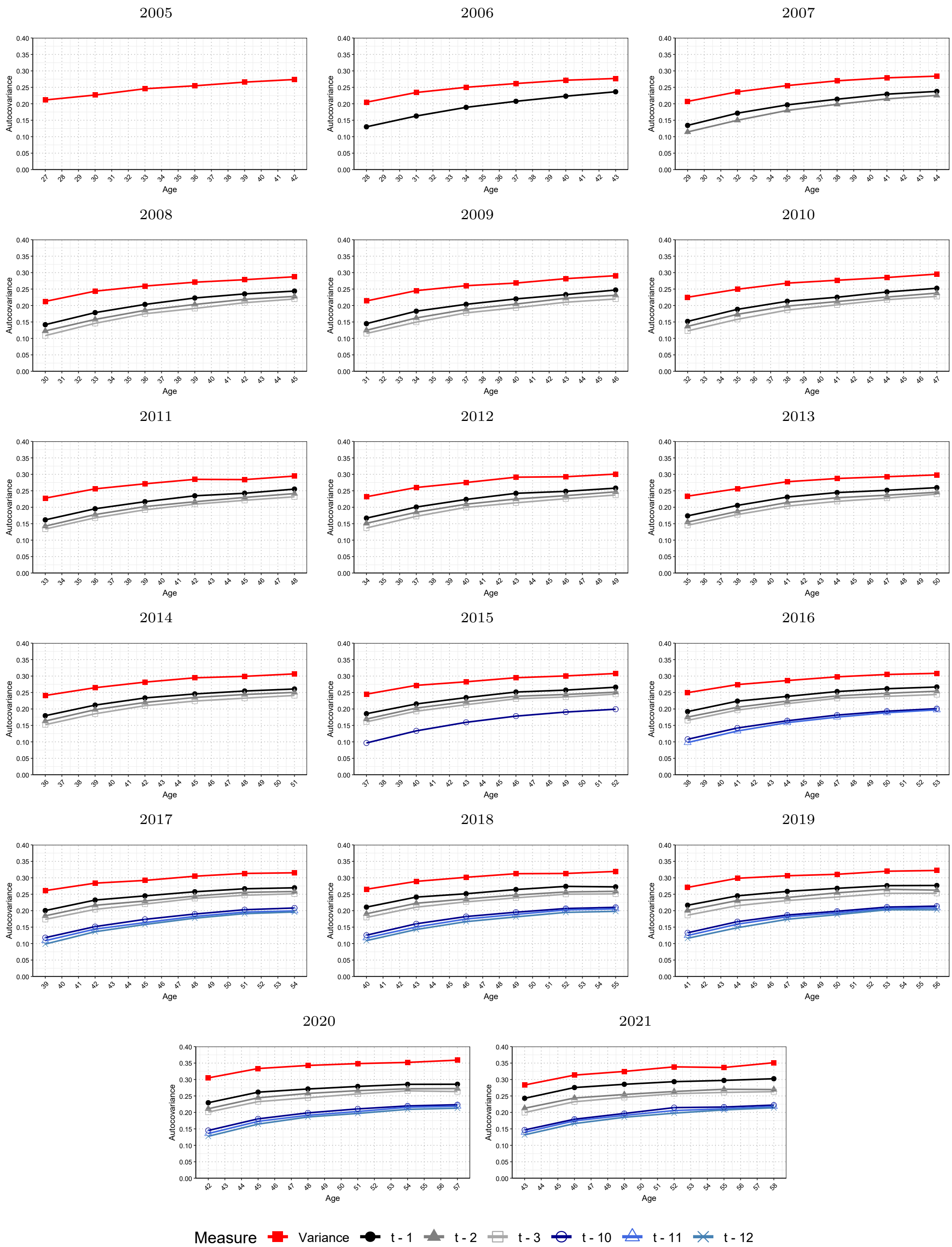
C Supplementary figures

Figure C1. Autocovariances by cohort



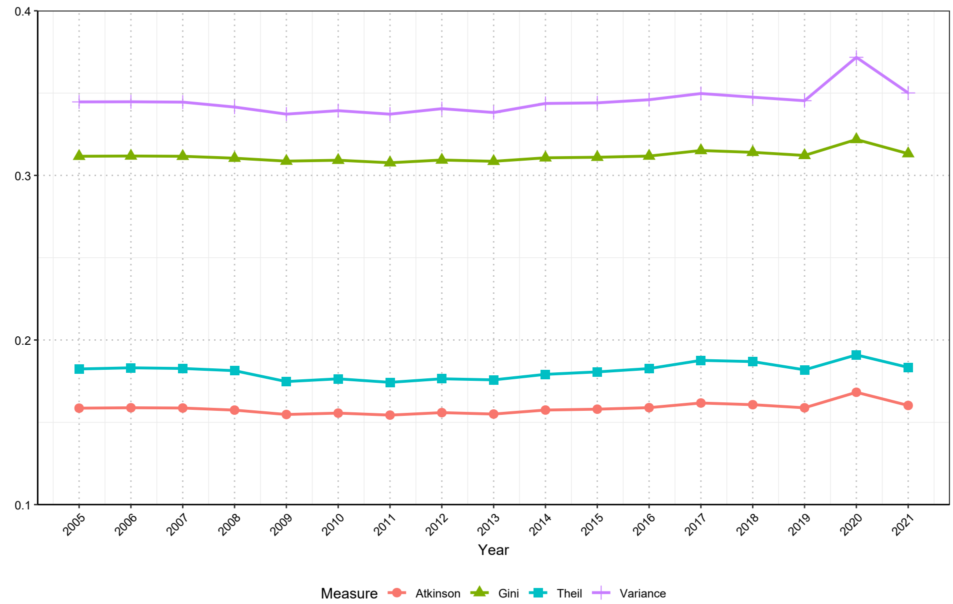
Note: The autocovariances of log residual earnings refer to $\text{Cov}(t, t-k)$, where t refers to the year and k refers to the lag.

Figure C2. Autocovariances by year



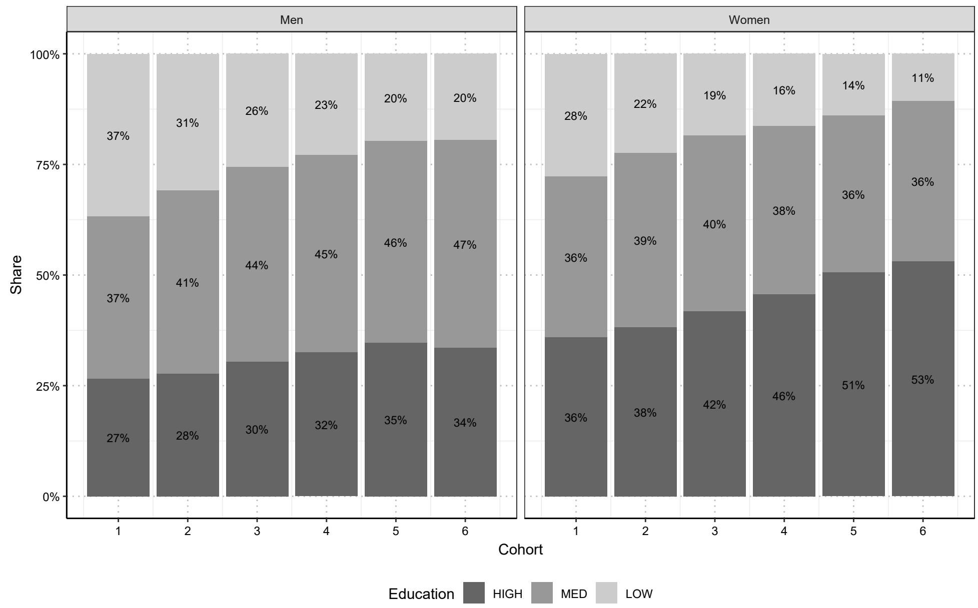
Note: The autocovariances of log residual earnings refer to $\text{Cov}(t, t-k)$, where t refers to the year and k refers to the lag

Figure C3. Earnings inequality among individuals of working age in Belgium, 2005-2021



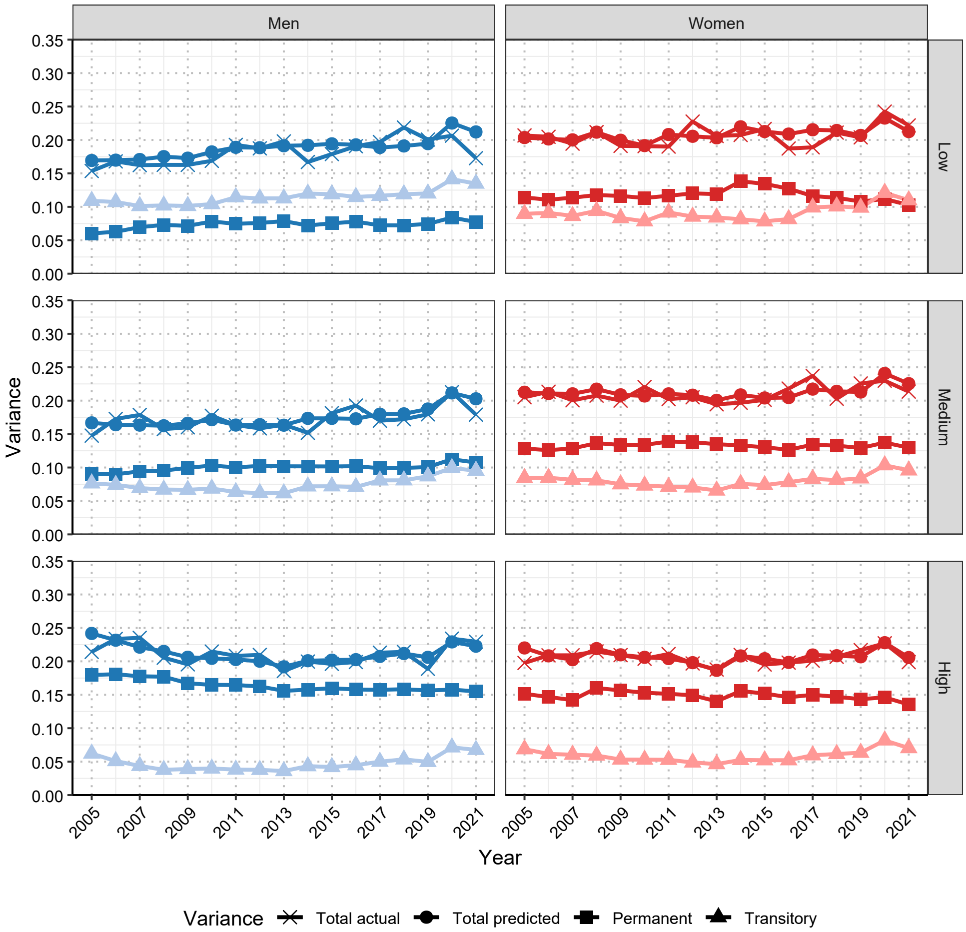
Note: The figure shows different inequality indices calculated on the entire 10% sample that is of working age (between the ages of 25 and 59 inclusive) who report earnings that are positive and above three times the minimum wage, including self-employed earnings. Atkinson (1), Gini and Theil indices are calculated on real gross earnings. Variance is calculated on *log* real gross earnings.

Figure C4. Education shares among employees by gender and cohort



Note: Birth years for respective cohorts: $C_1 = 1962 - 1964, C_2 = 1965 - 1967, C_3 = 1968 - 1970, C_4 = 1971 - 1973, C_5 = 1974 - 1976, C_6 = 1977 - 1980$. Shares apply to our restricted sample (i.e., working ages 25 and 59 inclusive, and employees who report only salaried earnings).

Figure C5. Variance decomposition, mid-career worker by gender



Note: The figure shows the trends in earnings inequality decomposed into its permanent and transitory components, for mid-career employees.