Earning dynamics in Sweden: The recent evolution of permanent inequality and earnings volatility*

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Abstract

This paper analyzes the dynamics of earnings over the life-cycle, based on Swedish data, and the evolution of permanent and transitory earnings inequality for 2002-2015. We use data on earnings from administrative records gathered in the ASTRID database. We find that features of the data does not match the predictions of the heterogeneous or restricted income profile models commonly applied in the earning dynamics literature and estimate an alternative permanent-transitory (PT) error components model. Analyzing the covariance structure of both male and female earnings, controlling for educational background, we find that the upward trend in permanent earnings inequality observed in Sweden during the 1990s does not seem to continue during the 2000s, and the financial crisis of 2008 did not have any major impact on the variability of earnings. We further simulate the accumulation of income pension entitlements and find that variations in pension entitlements is smaller among college educated workers.

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1 Introduction

The dynamics of individual earnings processes give crucial insights concerning individual ranking and mobility within the earnings distribution (e.g. Moffitt and Gottschalk, 1995; Haider, 2001; Baker and Solon, 2003; Gustavsson, 2007, 2008; Doris et al., 2013; Kässi, 2014). The findings of these studies reveal to which extent any observed changes in earnings inequality have been driven by convergence or dispersion of life-cycle earnings (permanent earnings), or by changes in earnings volatility (transitory earnings). For example, increased permanent inequality refers to a systematic widening of the earnings distribution (the relative earnings gap between high earners and low earners permanently increases), while increased transitory inequality implies increased mobility within the earnings distribution resulting in increased short-term earnings fluctuations.

To draw any extensive conclusions about what drives any observed patterns of earnings inequality, the earnings process has to be adequately decomposed into its permanent and transitory components. Increased permanent inequality could arise due to labor demand shifts from increased off-shoring and/or new technological paradigms, rendering skill depreciation of labor input in concerned sectors. An increase in permanent inequality might successfully be counteracted by policies targeting human capital investments over the life-cycle. Earnings volatility could, for example, be explained by changes in job instability due to labor market competition and/or hiring-firing restrictions, and is commonly approached with unemployment insurance to compensate for insufficient self-insuring measures.

This paper contributes to the literature by seeking evidence for the recent evolution of life-cycle earnings variability and volatility in Sweden. We employ data from the register database ASTRID, observing annual earnings for the years 2002-2015. This marks the first time that ASTRID data is utilized within this context, and the years included allow us to shed light on the potential impacts on the structure of earnings inequality caused by recent macro events, such as the great recession of 2008/2009 and the lingering Euro debt crisis. We also analyze the evolution of both male and female earnings inequality, contrasting the benchmark approach of only analyzing male earnings inequality. Lastly, as an extension of the analysis, we provide simulations of the distributions of income pension entitlements conditional on the estimated earning profiles. The relevance of such application comes from the notion of income pension entitlements being strictly derived from life-time pensionable income, for which earnings constitutes a considerable share for most individuals.

Since the 1960's, Sweden has experienced interesting and pronounced changes in observed earnings inequality. The 1970's saw a large decrease in pay differentials as the result of the solidarity wage policy, compressing the wage structure and subsequently decreasing earnings inequality. This pattern reversed throughout the 1990's with an observed increase in the cross-sectional variance of earnings during the recession of 1990-1994. These two events sparked the analyses conducted in Gustavsson (2007) and Gustavsson (2008), concluding that a decrease of permanent earnings inequality beginning in 1960 drove the subsequent compression of earnings, indicating that the role of the solidarity wage policy as the main explanation for the decrease in earnings inequality is not obvious.

Following the abandonment of centralized bargaining in 1983, Gustavsson's findings indicate that the subsequent earnings dispersion was driven by an increase in transitory inequality, questioning the explanation suggested in Edin and Topel (1997) that permanent earnings dispersion from increased incentives of individual human capital investments when abandoning the solidarity wage policy was the main cause for the observed patterns. The increased earnings dispersion that followed from the financial crisis of 1990-1994 was on the other hand found to have been driven by increased permanent earnings dispersion, with Gustavsson suggesting explanations such as an increase in the price of skill.

Income inequality has increased since the millennial shift, but the wage distribution has remained steadily compressed. Instead, the widened income distribution is argued to have explanations within increased capital income dispersion, and increased income differentials between employed and unemployed (Gottfries, 2018). While the financial crisis of 2008-2009 seems to have had little impact on the Swedish labor market as a whole, the recent evolution of the composition of earnings inequality remains unknown. It is, therefore, of interest to investigate the potential differences in how the financial crisis affected earnings inequality and volatility for men and women. The crisis is mainly argued to have had impacts on export industries in the private sector, while stable public finances negated any major shocks on the public sector. Given the greater female representation within the public sector, one could hypothesize that the financial crisis had a larger impact on the structure of male earnings inequality.

Despite its importance for policy design, and the good quality of register data available, only a few studies concerning earnings dynamics have been conducted using Swedish data. Sweden provides an interesting institutional setting for studying the composition of earnings inequality. The extensive public sector and collective wage bargaining could distort incentives for human capital investments and to exert effort in the long run (Edin and Topel, 1997). Additionally, the employment protection act (last hired-first fired) can be argued to decrease earnings risk for workers of longer tenure, but also to increase the number of temporary employment schemes and contribute to labor market segmentation. While there is no legal minimum wage, union contracts induces a wage floor covering most of the labor market. Since 1998, such contracts are negotiated on a highly coordinated basis between unions and employers' organizations.

Ultimately, we endeavor to estimate an empirical model that can fit the life-cycle evolution of earnings variability of Swedish employees, decomposed to distinguish between permanent earnings variability and earnings volatility. We find evidence for a parsimonious stationary earnings profile specification, serially correlated by an ARMA(1,1) process. Our results indicate that a large proportion of overall inequality can be attributed to transitory inequality, which notes the policy importance of complementary insurance measures such as social security to compress the earnings differential. A surprising finding is that permanent inequality does not seem to have increased of any substantial magnitude throughout the sample period. It is unclear to what extent human capital accumulation impacts the within-group life-cycle earnings inequality as we find that permanent earnings variability decreases over the life cycle. Our findings are not therefor not consistent with Mincer's human capital theory. Instead we find it probable that high variability of labor supply among younger workers due to part-time employment during human capital formation might outweigh wage effects of human capital accumulation. Further, the financial crisis of 2008 seems to have had no apparent impact on female earnings volatility, while a small increase in permanent and transitory inequality among men with less than high school and high school education is noted.

Simulations of income pension entitlements show that the within-group variability of income pension entitlements is larger for the population with less than high school education when compared to populations with higher educational attainment. This observation can probably be attributed to the fact that contributions to the income pension scheme is subject to an upper limit derived from the income base amount, which truncates contribution amounts of higher income groups. This holds true for both the males and females.

The remainder of the paper is outlined as follows. We survey a selection of relevant literature in section 2. Section 3 describes the data and descriptive statistics. We introduce the empirical model in section 4, followed by an outline of the estimation method in section 5. Results are presented in section 6. Section 7 contains the simulations of income pension entitlements. Section 8 concludes.

2 Literature review

Lillard and Willis (1978), Lillard and Weiss (1979), and MaCurdy (1982) made early and substantial contributions to longitudinal analyses on decomposing the individual earnings process into permanent and transitory components, establishing the foundations of the heterogeneous income profile (HIP) and restricted income profile (RIP) specifications and the scholastic disagreement following thereafter. The HIP model includes idiosyncratic earnings growth trends in the permanent component, following the theoretical foundation in Mincer's human capital theory. The RIP model rejects heterogeneity in income profiles and restricts permanent earnings to be governed by a unit-root process, implying that any earnings shocks are truly permanent. Hypotheses on profile specification are commonly tested based on inference from the covariance structure of earnings, where the permanent earnings component is identified from higher order autocovariances.

Lillard and Weiss (1979) suggested an empirical model of fixed and time-varying observable individual characteristics related mainly to labor market experience. This can be considered the prototype HIP model with stochastic shocks being modeled as serially uncorrelated innovations and subsequently instantly mean-reverting in the sense that deviations from the earnings growth trend have zero persistence. MaCurdy (1982) rejects the inclusion of individual heterogeneity in earnings growth in favor of an empirical model where the earnings process is governed by a unit root. Secondly, MaCurdy questions the common time series practice of treating initial conditions as known constants due to the relatively small finite time of panels of earnings. Instead, he considers random initial conditions to represent the conditions for the ARMA process initiation for a specific individual. This has implications for a model containing a unit root since any variance accumulated before labor market entry will be incorporated into the variance of the initial earnings, leading to an upward bias of estimated early life cycle earnings inequality. It is common to consider an initial persistent shock in the estimation procedure to capture the history of the time series prior to the observations to avoid biased estimates of the evolution of life-cycle earnings variability.

The disagreement concerning profile specification has remained throughout various contributions to the literature. Guvenen (2007, 2009) shows that if individuals are modeled to gradually learn about their earnings process in a Bayesian fashion, the autocovariance structure of the stationary HIP process would emulate the observed patterns of a RIP process (i.e. that autocorrelations are small and negative). He shows that not including individual earnings trends in the estimation, when they are in fact present in the real process, leads to an upward bias of the autoregressive parameter. In the case of high persistence of shocks, this might lead the econometrician to falsely select the RIP specification. Guvenen (2009) further documents residual earnings inequality to evolve in a convex fashion over the life-cycle, which is better fitted by the HIP process compared to the RIP specification.

Not limiting inference to be drawn solely from the autocovariance structure with regards to the identification of permanent and transtory has allowed for models of individual heterogeneity in more aspects than individual slope parameters. Meghir and Pistaferri (2004) incorporates ARCH effects in both permanent and transitory components, emphasizing heterogeneity in the earnings process beyond individual slope parameters. Browning et al. (2010) develops a model to account for unobserved heterogeneity by allowing for individual heterogeneity in shock variance, parameter estimates, stationary/non-stationarity, speed of convergence from initial value to the residual life-cycle process, as well as individual measurement error. Their study is based on a deliberately chosen homogeneous sample of danish workers from which they conclude that no one has a unit-root in their earnings process. They further claim that evidence suggesting a unit-root process in previous literature is due to the restrictions on heterogeneity. This does not however reject the presence of a unit root for all workers.

While Browning et al. (2010) declare present evidence to have accumulated against the RIP model, Hryshko (2012) rejects earnings growth heterogeneity from PSID data and deems the results of Guvenen (2009) as non-robust to any minor change in error specifications. Hryshko further contributes by showing that identification of a hybrid model (A combined

HIP/RIP model) is possible from small unbalanced samples[1]. The Hybrid specification is also suggested in Baker and Solon (2003). Kässi (2014) briefly discusses the consideration of such a model in his study on Finnish data, but questions its interpretability[2]. Gustavsson and Österholm (2014) approaches the stationary/non-stationary conundrum by employing the method of approximately median-unbiased estimation introduced in Andrews and Chen (1994). Inference drawn from a series of individual AR regressions and the resulting distribution of AR-parameters rejects the inclusion of a unit root in the true earnings process.

While analyses striving beyond inference from the autocovariance structure allow for models of more detailed earnings processes, it is motivated to keep models relatively simple for the purpose of utilizing the results in calibrations and simulations. While more detailed models would be able to explain the underlying causes that drive permanent and transitory earnings components, they go beyond the scope of solely decomposing recent evolution of earnings variability.

For the purpose of analyzing the evolution of permanent and transitory earnings variability, the factor analysis approach introduced by Moffitt and Gottschalk (1995) has been extensively employed in contemporary semi-parametric studies. By introducing time factor loadings, one could identify what has caused any observed change in inequality: changes in permanent earnings inequality, in transitory inequality or in both. The factor analyses approach has since been extended to allow for both time and birth cohort factor loadings, made evident in papers such as Doris et al. (2013) and Bingley et al. (2013).

Little work has been done on decomposing the evolution of earnings inequality in Sweden. Gustavsson (2007) examines the observed increase in earnings inequality following the recession of 1991-1994 throughout the 1990's. This was subsequently complemented in Gustavsson (2008) who examines the period of 1960-1990. Sweden famously experienced a substantial wage gap compression in the 1970's, which subsequently widened during the 80's and 90's. He employs data from the register database LINDA and

[1]Guvenen (2007) previously raised concern regarding the evaluation of the HIP-specification hypothesis based on inference from autocovariance moments calculated from small samples. This is elaborated upon thoroughly in Hryshko (2012).

[2]Identification of such a model is also not as straight forward due to the need to distinguish between the linear time evolution of the unit root from the linear time evolution of intercept/slope covariance. See equations 21-24 in appendix B.

concludes that permanent earnings inequality began to decrease before the introduction of the solidarity wage policy, possibly before 1960 which is the first year he observes. While a noticeable increase in earnings inequality coincided with the aftermath of the abandonment of central wage bargaining in early 1980's, Gustavsson finds this to have been driven by increased earnings volatility rather than by human capital dispersion. This could be considered a somewhat counterintuitive finding considering the solidarity wage policy to have discouraging effects on human capital investments, which should reverse when abandoning wage compression. Gustavsson (2007) determines the continued earnings dispersion of the 1990's was almost entirely driven by permanent earnings dispersion. The marked shift in earnings inequality took place during the recession of 1991-1994, evoking the question whether a shift from increased earnings volatility to human capital dispersion and cemented inequality might have taken place. It is interesting to note that Gustavsson (2008) finds earnings variance to evolve as a concave function of experience, a pattern incompatible with the random growth specification which implies a convex relationship. He settles with a RIP specification, despite it predicting earnings variance to increase linearly as a function of time, not in a strictly concave fashion. Furthermore, Gustavsson and Österholm (2014) finds evidence against the unit root specification, leaving any conclusions on adequate profile specification for analyses on Swedish workers pending. This ambiguity leads us to ask: (1) How has earnings inequality evolved more recently, and (2) what specification best represents the revealed evolution of life-cycle inequality of Swedish workers? We thereby contribute to the literature by seeking evidence for the recent evolution of life-cycle earnings variability and volatility in Sweden.

3 Data

We employ Swedish register data from the database ASTRID containing data for the Swedish population born between 1936-1997. Our data set include longitudinal data for 7,478,807 individuals observed for the period 2002-2015. ASTRID is a database linking geographical and socioeconomic information with information from tax records for the Swedish population for birth cohorts 1936-1997. It was compiled by Statistics Sweden (SCB) and hosted at the Department of Geography and Economic History at Umeå University (Stjernström, 2011). The main variable of interest was annual earnings defined as cash gross salary measured in 100 SEK, including wage and other compensations for labor, such as holiday allowances, shares from profits, travel reimbursements, and similar compensations. There is no truncation at the top in the measure of income in this data[3]. The sources of information are administrative records which have a number of advantages compared to survey data. Administrative records are free from non-stochastic sample attrition, apart from migration or death, meaning that it does not suffer from the same attrition issues frequent in survey data, such as the PSID. Furthermore since tax record information does not rely on the memory of the participants, this data should be less prone to suffer from measurement error due to misreporting. Employers are also legally obliged to report earnings amounting to more than 100 SEK to the Swedish tax agency (Skatteverket, 2019). While register data has been used in previous studies of the Swedish labor market [4], this is to our knowledge the first time that ASTRID data is used in this context.

3.1 Data selection

Only employees are considered[5], the self-employed are not considered during the years of self-employment due to tax incentives to define earnings as capital gains rather than labor income and the possibility of private consumption veiled as corporate expenses[6]. Additionally, seamen are excluded since their earnings are not necessarily registered in Sweden and would therefore not appear in our tax record data. Any zero earnings reported are treated as missing observations[7]. We utilize two data selection processes, one referred to as "strict" and the other as "lenient". The strict selection uses a set of data selection criteria based on those found in the literature. This makes it easier to compare our findings with the previous literature. The lenient selection functions as a control giving a measure of the sensitivity of the results to some potential selection effects.

The strict sample only considers prime age workers between 25-55 years of age, with valid data on educational attainment. There is no consensus

[3]An issue in Kässi (2014) for example.

[4]See for example Gustavsson (2007) and Gustavsson (2008).

[5]Employed in both the public and the private sectors. Some, for example Bingley et al. (2013), exclude employees in the public sector and workers with part time employments from their analyses. Due to institutional factors, such as collective bargaining being the norm in Sweden, we would argue that the labor market functioning in the public and private sector are relatively similar. Not excluding the part-time employed is motivated by earnings, and not wages, being the variable of interest in our analysis.

[6]Other examples of studies solely considering employees are for example Meghir and Pistaferri (2004), Kalwij and Alessie (2007) and Bingley et al. (2013).

[7]This was a result of the logarithm of earnings being the focus of the analysis.

in the literature regarding the range of ages relevant for consideration in these type of models. Our chosen range of ages 25-55 is used by Meghir and Pistaferri (2004) and Bingley et al. (2013). This age span was chosen as we wanted to focus on individuals with relatively stable labor supply. That only individuals ages 25 and above are considered reduces some the additional variability in earnings caused by individuals who combine work with higher education. The upper bound reduces the probability of individuals either fully or partially retiring. Other examples are Baker (1997) who included all aged 21-64 and Gustavsson (2008) who included individuals aged 26-53. The lenient selection required that individuals have valid data on education, was at least 25 years old and were born between 1956-1981. This means that the range of ages observed increases to 25-59, there was no other requirements for this sample. The restrictions for the lenient sample was made to allow for comparability of the results with the strict counterparts.
Variation across as well as within cohorts is exploited for the estimation of the parameters of interest, which increases the importance of the definition of sample selection criteria by year of birth. We require that each cohort has at least ten years of viable observations. Bingley et al. (2013) and Sologon and Van Kerm (2014) use this criteria. It aims to ensure sufficiently long periods of observations by cohort. Others have used variants of this approach, for example Baker and Solon (2003) require 9 years of observations per cohort and Gustavsson (2008) require 6. A consequence of our 10 year criteria is that only individuals born between 1956 and 1981 are considered in the analysis. This reduced the sample size from 3,692,143 to 1,678,904 women and from 3,786,664 to 1,745,167 men. This criteria combined with the criterion for age meant that some cohorts were not observed all periods in the strict sample. That some cohorts are not observed for all periods makes the panel unbalanced. The lower bound on age means that individuals born after 1977 were disregarded for one or more periods. For example, individuals born 1978 were not included 2002 and those born 1981 were not considered over the period 2002-2005. There is a similar truncation as a result of the upper bound on age which affected the cohorts born between 1956-1959. In the strict sample, those born 1959 were not considered 2015, and the ones born 1956 were disregarded over the period 2012-2015 in the strict sample. Individuals born between 1960 and 1977 are not affected by the restriction on age in the strict sample.

Individuals are allowed to leave and enter the data on a year to year basis depending on whether or not they fulfill the criteria during the specific period. This feature is sometimes referred to as the panel being "revolving". Haider (2001) introduced the terminology of the "revolving unbalanced panel" sometimes used in the literature to describe panels where all cohort are not observed for all periods and where individuals may enter and exit freely. This approach mitigates parts of the problem of including females in the analysis since any maternal leave longer than one year is treated as a missing observation like long term unemployment Kässi (2014). To analyze both women and men is relatively uncommon in the literature which primarily focuses on male earnings. Men and women were analyzed separately since their earnings processes are expected to differ and for increased comparability of our results with the previous literature.

To ease the identification of individual earnings profiles, each individual was required to have valid earning observations for at least five consecutive years in the strict sample following Bingley et al. (2013). Various criteria restricting the sample to individuals observed to those relatively well established on the labor market have been employed in the literature. Other examples of similar criteria are restricting the sample to those observed all years as Baker (1997), only considering individuals that are observed at least 9 years (not necessarily consecutive) as Meghir and Pistaferri (2004) or removing those with 5 or more years of inactivity like Sologon and Van Kerm (2014). We chose the criteria of Bingley et al. (2013) for our strict selection, this restricts the analysis to workers well established on the labor market. This criteria reduced the sample size to 1,317,692 men and 1,330,532 women, omitting 427,475 and 348,372 individuals respectively.

The top and bottom 0.5% of the yearly income distribution was removed in the strict sample. This truncation of the distribution of earnings is used to reduce the influence of outliers. Limitation of extreme observations has been employed in the literature by e.g. Kalwij and Alessie (2007), Bingley et al. (2013) and Lochner and Shin (2014) using a 0.1%, 0.5% and 1% limit respectively. Other methods of reducing the impact of extreme observation has been used by previous researchers, for example Haider (2001) removed observations with too high or low hourly wages based on fixed criteria and a similar approach (although for earnings) was used in Baker and Solon (2003). Gustavsson (2008) used another alternative method, a criteria based on the size of earnings in relation to the Swedish "basic amount".

Males and females were separated into groups based on years of education. Empirical moments were calculated separately for these groups. The gender and years of education groups were aggregated to larger groups when we fitted the model. These education groups were individuals with less than high school education (7-9 years of education), with high school education

(11-12 years of education), with at least some college education (13-14 years of education), with a college education (15-17 years of education) and with participation in doctoral studies (19-21 years of education). Individuals with doctoral studies were not analyzed in this article. Reasons behind this decision were that stipends for educational purposes are not classified as taxable income in Sweden, and would therefore not be included in our measure of earnings. The number of individuals with this type of education was relatively small, especially among the younger birth year cohorts. We analyzed these groups separately as the labor market characteristics may differ for these groups. In our view the functioning of the labor market may differ for individuals with various levels of education, for example the type of jobs available and the substitutability of labor. The education level also provide a proxy for human capital accumulation, as this does not directly enter our theoretical model[8].

Overall the strict filter reduced the sample size to 1,285,470 males and 1,309,667 females. Compared to the literature this can still be considered a relatively large sample [9]. Sample sizes in total and for each education group can be found in Table 1. It is important to note that the strict selection seem to disproportionately affect the less educated population. This could potentially be a sign of non-monetary returns to education, such as job security and smoother transitions between jobs or between employment and unemployment.

[8]See chapter 4.3.

[9]A previous study in Sweden using register data, Gustavsson (2008), analyzed data for 76,079 individuals and the sample utilized in for example by Haider (2001) consisted of only 3,115 individuals drawn from the PSID. Blundell et al. (2015) analyzed data for 934,704 Norwegian men and provide an example of a study using a panel with comparable scope.

	Men		Women	
	Strict	Lenient	Strict	Lenient
All	1,285,470	1,581,177	1,309,667	1,565,469
College	279,736	326,934	432,163	480,385
Some College	197,311	236,550	204,521	238,830
High School	644,987	781,164	568,107	671,968
Less than HS	138,201	207,750	85,873	152,987
Doctoral	25,235	28,779	19,003	21,299

Table 1: Sample sizes by gender, selection criteria and education groups:
Note: Individuals without valid data on education are not included in any sample.

3.2 Macro facts

Figure 1 depicts yearly average log earnings for men and women, both overall and by educational group, for the period 2002-2015. This period include recent macro economic events such as the aftermath of the dot-com bubble of 2001, and the 2008 financial crisis. Note that there could be potential selection effects from the sample aging over the period and that earnings are in nominal terms when interpreting this figure. For both the male and female samples there are differences in average log earnings between educational groups, The most pronounced are the difference between high school and college educated. Average log earnings are higher for the strict samples compared to the lenient samples. Males in the strict sample earns on average 1.5% more than their lenient counterparts, this number is 1.3% for females. There is also a difference in mean log earnings for men and women worth mentioning. Comparing the average earnings for women and men over all education groups in Figure 1 and year one find that women's earnings are on average 95.0% of their male counterparts in the strict sample and 94.9% in the lenient. The trends observed for the different data sets are overall similar with comparable locations.

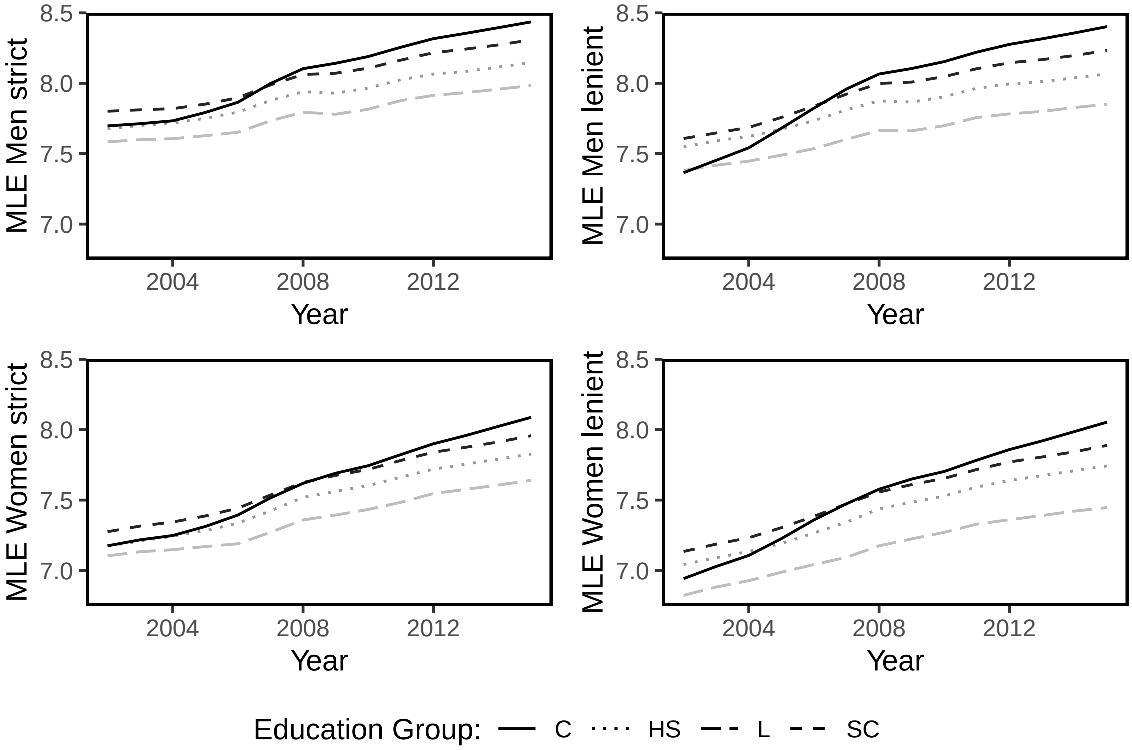

Figure 1: Average log nominal earnings 2002-2015
Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

Figure 2 presents the trends in variance of log earnings 2002-2015. The most striking feature is the downward trend in variance over the years. This downward trend can be partly explained by selection. As one can observe in figure 3 and appendix A, we found that variances in income had a tendency to decrease over the early to middle part of the working life. Since we do not include individuals born after 1981, the share of young workers with relatively high earnings volatility decreases over time. Gustavsson (2007) found a similar age pattern in the variance of the transitory component of earnings in Sweden during the 90's. The relatively large drop in variance found among the college educated over the first few years can to some extent be explained by individuals working part-time while still attending college. A similar initial drop in variance was found among High-Skilled Norwegian workers by Blundell et al. (2015). The pattern with decreasing variances over long periods of the life-cycle is at odds with the theoretical predictions of the commonly applied HIP and RIP models. Both of these models predicts increasing variances over the life-cycle, the HIP predicts a weakly concave increase while the RIP predict a linear increase. The HIP allows for a temporary drop in variances early in the life-cycle through a negative covariance between the heterogeneous intercept and growth terms. A negative covariance cannot however outweigh the effects of the heterogeneous growth rates in the long run due to the limits of correlation.

Variances in the lenient data are larger, as one would expect, with the largest difference found among the individuals with less than high school education. For each gender the lenient and the strict samples seem to follow similar general trends although there is some differences between the genders. The most pronounced is found among the college educated, for men the variances are initially higher and decreases rapidly until 2008. Although a downward trend in variances is found among college educated women, the decrease is less dramatic. An interesting feature is that the variance of earnings for women seem to be less affected by the financial crisis of 2008. One possible explanation could be the choice of sector of employment differing between men and women. More women than men are employed in the public sector (Statistics Sweden, 2019), which is likely to be less sensitive to market fluctuations. There is also evidence suggesting that the choice of field of education differ between men and women and that women to a larger extent choose degrees related to health and education (Daymont and Andrisani, 1984; Zafar, 2013). These sectors could be considered as being less sensitive to business cycle fluctuations which could partially explain the observed difference between men and women. The variances for the more educated seem to have been affected less by the crisis, this could be due to non-monetary returns to education such as increased job security.

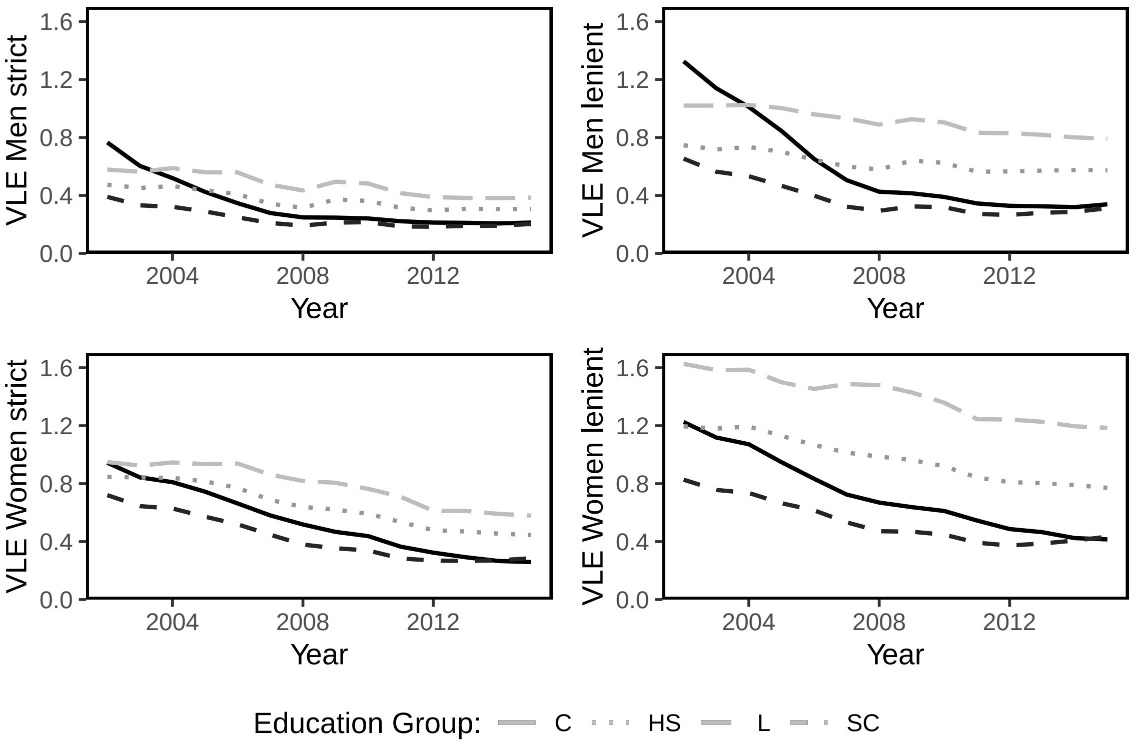

Figure 2: Variance log nominal earnings 2002-2015
Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

3.3 Empirical covariances

Figure 3 shows the variance and first three autocovariances for college educated males from the strict data as an example. The tendency of decreasing variances in earnings over the life-cycle observed in the data was an unexpected finding. Most of the literature, the permanent income hypothesis, and both HIP and RIP models suggest that variances increases with age or (potential) experience. Similar patterns were found in the other education groups and for females as well in the strict data (see Figures 8 - 11 in Appendix A). For women in the lenient selection, the variances start to increase again after the age of 55 and for men with high school education it start to increase around the age of 45. The remaining male education groups in the lenient data follow patterns similar to the strict data. Deaton and Paxson (1994) found that inequality in earnings was increasing with age in Great Britain, the United States and Taiwan. Blundell et al. (2015) found upward trends in the variance of earnings over the life-cycle for the low- and medium skilled male workers in Norway, while for the high skilled they found a steep downward trend in the early stages, followed by a period of relative stability with fairly small changes in earnings variance. This pattern is similar to that found in our data. In his analysis of Finnish earnings Kässi (2014) found upward trends in earnings variance over the life-cycle among men and downward but less pronounced trends among women. The pattern of variances increasing as individuals approaches retirement is commonly observed in the literature. A plausible explanation could be that the supply of labor becomes more variable during this part of the life-cycle.

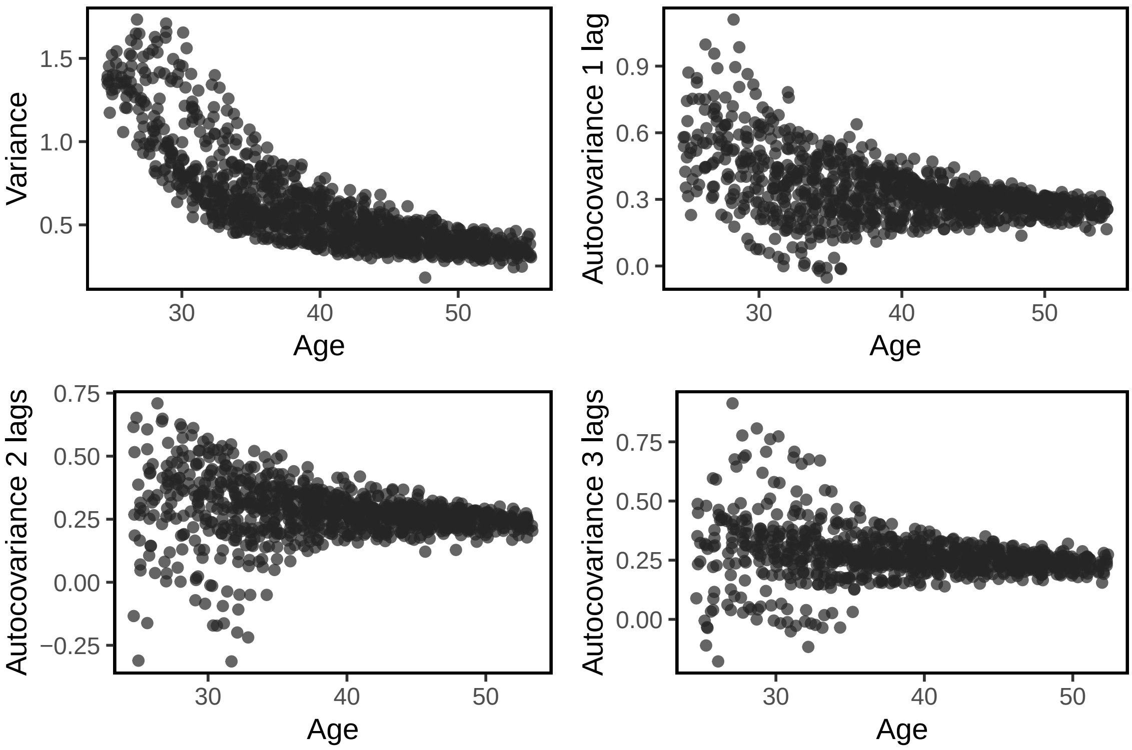

Figure 3: Variance and first to third lag autocovariance of log earnings for males in the college educated strict sample. Each data point in the represent the empirical variance,or autocovariance, of earnings for a specific birth year and years of education group at a certain age.

Note: Plots for the variance and first three autocovariances for all analyzed groups can be found in Appendix 7.1.

4 Model

We analyze the dynamics of the residual log earnings in this paper. Many of the social security systems in Sweden, such as pension, unemployment benefits, and parental allowance, have benefits based on income and earnings rather than wages. This makes earning dynamics relevant from a policy perspective. That collective bargaining is the norm and as Sweden has a rigid wage structure (Gottfries, 2018) provide further argument for analyzing earnings. By analyzing earnings rather than wages one capture two dimensions of inequality: inequality of wages and inequality in hours worked (Kässi, 2014).

4.1 Calculation of residual earnings

The residuals, $\hat{y}_{cide}$, were calculated by removing the yearly means for each birth cohort- and years of education subset of the data. This "de-meaning" approach to estimate residual earnings follows from Baker and Solon (2003). As the covariance structure of earnings is the focal point of our analysis, the residual earnings are sufficient for identifying the parameters of interest. In this paper the residuals are defined as:

$$\hat{y}_{cide} = Y_{cide} - \overline{y}_{cde} \tag{1}$$

Where Y_{cide} is the observed log of earnings calendar year d for individual i born year c with e years of education and $\overline{y}_{cde}$ is the year and group specific sample mean. An alternative method for estimating the residual earnings is running a separate first stage regression using observable characteristics (e.g. Lillard and Weiss (1979) and Meghir and Pistaferri (2004)) sometimes including polynomials in potential experience or age (see Haider (2001) and Blundell et al. (2015)). We chose to follow the approach of Baker and Solon (2003) as it flexibly captures the macro, age and cohort effects on earnings levels we wish to control for. The subindex e will be suppressed when discussing the theoretical model and population moments as all years of education subgroups were modeled the same way.

4.2 Earnings decomposition

Consider the following general model of individual residual log earnings, $\hat{y}_{cid}$:

$$\hat{y}_{cid} = y^P_{cid}(\alpha_i, \beta_i, X_{id}) + y^T_{cid} \tag{2}$$

Where the permanent component is denoted as y^P_{cid} and encapsulates the individual earnings profile while y^T_{cid} represents the transitory component. Let α_i correspond to individual specific intercepts, a parameter capturing permanent differences in earnings among individuals. This is common for both HIP and RIP model specifications and central in our. One could consider α_i to measure differences in innate ability or earnings potential among individuals. The HIP model includes the individual slope parameter, β_i, that regulate individual earnings growth over the life-cycle. This is sometimes modeled as an effect of human capital accumulation through experience or as an age effect. In the first case X_{id} represents the individual level of experience a given period (e.g. Bingley et al. (2013)) and in the second it simply represents age (see e.g. Baker and Solon (2003)). Experience is usually measured as potential experience, i.e years since labor market entry or age minus years of education, which means that there is a perfect collinearity between an individuals age and experience causing difficulties combining the two in the same model. In conformity with human capital theory such as Mincer's theory on life cycle earnings and the on-the-job training hypothesis, earnings growth rates, β_i, are usually allowed to be correlated with initial earnings, α_i. If the covariance is negative it would support the idea of the Mincer cross-over.

The RIP process would reject individual growth trends in favor of a purely statistical random walk specification. These types of models are calibration friendly, but lack economic rationale. In the less frequent case of adopting a model with both a random growth and a random walk component in the permanent component, the evolution of earnings would follow a random walk with a drift. Estimation of these types of models has occurred in the literature (e.g Baker and Solon (2003)), however the interpretation of the covariance term is less clear with this mixed specification as both the covariance between α_i and β_i and the variance of the random walk shock evolves linearly over time, potentially in opposite directions.

The transitory component, y^T_{cid}, is a purely stochastic term capturing earnings shocks that decay swiftly or moderately. This is commonly achieved by allowing for serial correlation, such as an ARMA(p,q) process where the AR(p) components captures persistent shocks, and the MA(q) components captures swiftly decaying shocks.

4.3 Model specification

We propose an empirical model with a condensed individual life-time earnings profile. This model can be seen as an augmentation of the one proposed by Lillard and Willis (1978)[10]. We define the transitory component in our model as an ARMA(1,1) process with cohort- and time factor loadings and a separate labor market entry shock.

$$\hat{y}_{cidt} = \lambda_c \gamma_d \alpha_i + \mu_c \pi_d \tau_{it} \tag{3}$$

$$\tau_{i0} = \xi_i \tag{4}$$

$$\tau_{i1} = \rho \xi_i + \epsilon_{i1} \tag{5}$$

$$\tau_{it} = \rho \tau_{it-1} + \epsilon_{it} + \theta \epsilon_{it-1} \tag{6}$$

$$[\alpha_i, \epsilon_{it}, \xi_i] \sim \big([0,0,0],\ [\sigma^2_\alpha, \sigma^2_\epsilon, \sigma^2_\xi]\big)$$

In Expression (5), λ_c and μ_c are cohort specific factor loadings scaling the permanent and transitory variances between cohorts. The variables γ_d and π_d corresponds to time factor loadings that allow for scaling from calendar year specific macro shocks. We used factor analysis in our model since it allows for permanent and transitory earnings variances to depend on the calendar year and birth cohort. In this model, index t corresponds to years of potential experience, measured as years since labor market entry[11]. The indexation for years of education, e, have been dropped to ease the notation.

The permanent component is parsimoniously specified simply as α_i. This parameter is assumed to be distributed with mean zero and variance σ^2_α. As there was no clear trend with earning variances increasing with age, neither linearly nor in a convex manner, the RIP and HIP specifications of the permanent wage would impose structures on the data that do not match the patterns observed. This made it difficult to justify the use of these types of models. Regarding effects from human capital, this is partially controlled for by separate analysis of different education groups and α_i. The commonly applied human capital models in the earnings dynamics literature does not allow for earnings converging over the life-cycle. We do however allow for some heterogeneity in the permanent component through the factor loadings.

[10]The inclusion of a separate initial shock, cohort- and time factor loadings and a transitory component modeled as an ARMA separates our residual earnings model from that of Lillard and Willis (1978)

[11]Defined as age - 25 in this model.

The transitory component, τ_{it}, is modeled as an ARMA(1,1) where the autoregressive (AR) parameter is denoted ρ, θ represents the moving average (MA) parameter and innovation term is defined as ϵ_{it}. The innovation term is considered to strictly adhere to earnings shocks and is assumed to be distributed with a mean of zero and variance σ_ϵ^2. We aim to capture the initial drop in variance of log earnings observed in the data by including a shock upon initial entry on the labor market ξ_i. This initial shock will have some persistence through the AR(1) process and is assumed to have a zero mean distribution with the variance σ_ξ^2. While the structure of the transitory components conforms with much of the contemporary literature the specification of the permanent component shares more similarities with the model of Lillard and Willis (1978), as it does not include any trend or non-stationarity in the permanent component.

5 Estimation method

The properties of life cycle earnings are commonly identified by drawing inference from the observed covariance structure of earnings. We used the general method of moments (GMM) for our estimations. This is a common method for estimation within the literature[12]. There are numerous reasons why GMM is so widely adopted within this literature. GMM can cope with endogenous regressors, over-identification, and relies on a relatively sparse set of statistical assumptions. The basic principle is to match the information observed in the data (the empirical moments) with the predictions made from a theoretical model (the population moments) so that the distance between them are as small as possible. An advantage GMM has over the alternative maximum likelihood (ML) approach is that it does not have to rely on distributional assumptions for the underlying unobserved counterpart. As the first order moments are 0 by construction, its utilization does not require any assumptions regarding the distribution of shocks, which previous evidence suggest not to be normal[13].

The empirical moments used in this paper are the estimated second order moments of the residual logarithm of earnings. The moment conditions were calculated separately for each years of education subgroup, and then combined into the education groups. The cohorts included in the samples

[12]See Baker and Solon (2003), Gustavsson (2008), Bingley et al. (2013), Kässi (2014) and Blundell et al. (2015) for examples of similar studies employing GMM in their estimation.

[13]Lillard and Weiss (1979) observe slightly left-skewed, fat-tailed errors, and Horowitz and Markatou (1996) also concludes non-normally distributed innovations.

were observed for 10-14 periods yielding 55 to 105 second order moments per subgroup. We present the variance and first three autocovariances in log earnings aggregated and by education group in Appendix A. Estimates of empirical moments based on fewer than 30 observations were disregarded from the analysis. This mainly affected individuals with an 8 year primary education education[14]. The theoretical second order moments implied from the model presented in chapter 4.3 and used for identification of the parameters will be presented below. The variances from the theoretical model are:

$$V_{cd0} = \lambda_c^2 \gamma_d^2 \sigma_\alpha^2 + \mu_c^2 \pi_d^2 \sigma_\xi^2 \tag{7}$$

$$V_{cd1} = \lambda_c^2 \gamma_d^2 \sigma_\alpha^2 + \mu_c^2 \pi_d^2 (\rho^2 \sigma_\xi^2 + \sigma_\epsilon^2) \tag{8}$$

$$V_{cdt} = \lambda_c^2 \gamma_d^2 \sigma_\alpha^2 + \mu_c^2 \pi_d^2 \left(\rho^{2t} \sigma_\xi^2 + \sigma_\epsilon^2 \left(1 + (\rho + \theta)^2 \frac{1 - \rho^{2t}}{1 - \rho^2} \right) \right) \tag{9}$$

The 0 indexation refers to the first year after labor market entry. The theoretical moments for the autocovariances are:

$$AC_{cd0s} = \lambda_c^2 \gamma_d \gamma_{d+s} \sigma_\alpha^2 + \mu_c^2 \pi_d \pi_{d+s} \rho^s \sigma_\xi^2 \tag{10}$$

$$\begin{aligned} AC_{cd1s} &= \lambda_c^2 \gamma_d \gamma_{d+s)} \sigma_\alpha^2 \\ +\mu_c^2 \pi_d \pi_{d+s)} &\left(\rho^s \left(\rho^2 \sigma_\xi^2 + \frac{\rho + \theta}{\rho} \sigma_\epsilon^2 \right) \right) \end{aligned} \tag{11}$$

$$\begin{aligned} AC_{cdts} &= \lambda_c^2 \gamma_d \gamma_{d+s)} \sigma_\alpha^2 \\ +\mu_c^2 \pi_d \pi_{d+s} &\left(\rho^s \left(\rho^{2t} \sigma_\xi^2 + \sigma_\epsilon^2 \left(1 + (\rho + \theta)^2 \frac{1 - \rho^{2t}}{1 - \rho^2} \right) \right) \right) \end{aligned} \tag{12}$$

The index s refer to the number of lags from calendar year d. These theoretical moments constitute the elements of the theoretical autocovariance matrix, $\Omega(\Theta)$. Let $\omega(\Theta)$ be the half vectorization of $\Omega(\Theta)$. These were matched with our vectors of group specific estimates of corresponding empirical moments, denoted $\hat{\phi}_{ce}$. The index e denotes years of education. For

[14]This particular type of primary education called "Realskola" disappeared from the schooling system in 1970.

a given birth cohort and years of education group the vector of moment conditions are:

$$g_{ce}(\Theta) = \mathbb{E}\big[\phi_{ce} - \omega(\Theta)\big] \tag{13}$$

The groups were based on year of birth and length of education and Θ represent the set of parameters from the theoretical model. The empirical moments were replaced by their sample counterpart ($\hat{\phi}_{ce}$) and the expectation by the sample mean in the estimation. The vectors of moment conditions were then aggregated to $g(\Theta)$, which contained the moment conditions for all birth year cohorts and relevant years of education groups. The objective minimized was the following:

$$Q(\Theta) = g(\Theta)'Wg(\Theta) \tag{14}$$

W is a symmetric positive definite matrix, sometimes referred to as a weighting matrix, which defines the distance between observed and theoretical quantities. Identification requires that the probability limit of the GMM objective function is uniquely minimized by a vector of parameter values, Θ_0. If this is the case and the data are such that a law of large numbers apply then the GMM estimator is consistent and asymptotically normal. In theory any symmetric positive definite matrix could define W and yield consistent estimators. One method is to use consistent estimates of the covariance matrix of the moment conditions as W, for example the two-step GMM proposed by Hansen (1982). This method is asymptotically consistent and efficient, but has been found to be biased in small samples (Altonji and Segal, 1996; Clark, 1996). Evidence suggest that the bias is increases when estimating models with a large number of overidentifying restrictions or when fitting a model to data drawn from distributions with fat-tails (Altonji and Segal, 1996). Our models have a large numbers of overidentifying restrictions and Lillard and Weiss (1979) found evidence suggesting that shocks to earnings could be drawn from skewed and fat-tailed distributions. The size of the weighing matrix provided some additional practical problems to implement optimal GMM, each of the 25 birth year cohorts produce up to 105 moment conditions and all education groups include at least two years of education subgroups for which the empirical moments have been calculated separately. This dissuaded us from implementing optimal GMM in our estimations.

The equally weighted minimum distance (EWMD), where W is defined as the identity matrix, is an alternative method commonly used in the literature related to the covariance structure of earnings[15]. Baker and Solon (2003), Gustavsson (2008), Bingley et al. (2013) and Blundell et al. (2015) are examples of studies employing this method for estimation. This approach was considered but not implemented for this paper. There was large variations in the size of the underlying sample when calculating the empirical moments, these sub-samples had sizes ranging from 30 to 23017 individuals. Our view is that the inference should be drawn from where the evidence is the strongest and using EWMD would mean that all moment conditions are given the same importance regardless of the precision of the estimate or the size of the underlying sample for estimation[16]. The moment conditions were instead weighted using a diagonal matrix with the inverse of the variance of the empirical moments. As a result, the more precisely estimated empirical moments are given priority in the optimization. The smaller the standard error for the empirical moment the larger the value of the moment condition becomes[17].

All statistical computations where conducted with the software R and the package "BB" was used for the optimization procedure. Standard errors were calculated using the delta method. This method uses a first order Taylor approximation and the asymptotic normality of the estimator to approximate the variance of the estimates (see Oehlert (1992) for a review of the method).

6 Results

The core parameters of the residual earnings model are presented in Table 2 for male samples and Table 3 for females. The proportion of overall earnings variance attributable to permanent inequality by birth year cohort is presented in figure 4 while estimated cohort and time factor loadings are presented in figures 5-8. This was done to present the trends over time and between cohorts more clearly. In Appendix D the distribution of observed- and predicted moments is presented for each analyzed subsample. This allows for comparison between the observed and predicted moments and demonstrates

[15]For a more general discussion see Chamberlain (1983).

[16]We tested the estimating procedures using EMWD and using the some college males subset of the data and found that the estimates for the strict selection were robust to a change in the weighing matrix.

[17]We checked the sensitivity for the choice of weighting matrix and estimated the model using EWMD for the male and female cohorts with some college education from the strict sample and found that the results, apart from the signs of the MA(1) parameters, were qualitatively unaffected.

how the model fits the data. The full set of estimated birth cohort and time factor loadings can be found in Table 4-7 in Appendix E.

6.1 Core model

One important parameter in the core model is the variance of the heterogeneous intercepts, σ_α^2. A pattern common to both genders is that the variances are higher for the lenient selections compared to their strict counterparts. A possible explanation of this difference is the selection of individuals relatively well established on the labor market [18]. This can be related to the finding of Gottfries (2018) that increasing income differentials between employed and unemployed can partly explain observed increases in income inequality, while wage differentials have remained seemingly rigid. There is an interesting difference in the patterns for women and men regarding the estimates of σ_α^2. For men, the variance of the permanent earnings differences seem to be increasing with education while there is a tendency toward an opposite pattern for women. The difference in the effect of education between men and women is a bit puzzling but could potentially be a result of factors such as choice of fields for education or line of business being different between men and women on an aggregate level. For instance, women are to a larger extent than men hired in the public sector, with an overrepresentation primarily in employments at county and municipal level (Statistics Sweden, 2019). These sectors have a more compressed wage structure than the private sector in Sweden (Statistics Sweden, 2018).

Analyzing the AR(1) parameter estimates, one find that all estimates are significantly smaller than unity. This is in conformity with the findings of Gustavsson and Österholm (2014) that Swedish earnings are not governed by a unit-root process. The estimates are all positive and relatively small for all samples, sizes ranging from 0.335 to 0.441. These estimates for the AR(1) parameter are smaller than that of Gustavsson (2007), who found an AR(1) of 0.555, and of Gustavsson (2007) who found an AR(1) parameter of 0.8190 for years 1960-1967, and 0.5726 for 1968-1990. Our estimates for the AR(1) parameter is similar in size to those found by Lillard and Willis (1978). The AR(1) parameter can be interpreted as regulating the effects

[18] The requirement of five consecutive years of valid observations for earnings excludes individuals that are more prone to being long term unemployed as well as individuals that regularly switch between being self-employed and employed. One could argue that transitions in and out of employment, or in and out of self-employment, could have long term effects on earnings that are not captured in this model.

	ρ	θ	σ^2_α	σ^2_ϵ	σ^2_ξ	Prop. Perm	MSE
Less than HS strict	0.377***	-0.048***	0.126***	0.184***	0.277***	0.358	0.029
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.008)	
Less than HS lenient	0.351***	-0.057***	0.175***	0.482***	0.622***	0.281	0.041
	(0.003)	(0.001)	(0.001)	(0.006)	(0.008)	(0.049)	
High School strict	0.388***	0.009***	0.135***	0.204***	0.329***	0.380	0.008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.001	
High School lenient	0.350***	-0.022***	0.205***	0.525***	0.800***	0.313	0.011
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	
Some College strict	0.411***	0.004***	0.152***	0.167***	0.238***	0.407	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	
Some College lenient	0.375***	0.005***	0.209***	0.441***	0.654***	0.351	0.006
	(0.001)	(0.000)	(0.000)	(0.004)	(0.005)	(0.024)	
College strict	0.335***	0.067***	0.196***	0.199***	0.237***	0.421	0.013
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.009)	
College lenient	0.441***	0.020***	0.268***	0.509***	0.602***	0.394	0.028
	(0.001)	(0.000)	(0.000)	(0.007)	(0.008)	(0.044)	

Table 2: Results core parameters for Male Samples.
Note: $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$. *All hypothesis tests are two-sided. Standard errors are presented in brackets beneath parameter estimates. Prop. Perm measures the mean ratio between predicted permanent variance and the sum of predicted permanent- and transitory variances. MSE is mean squared error between predicted and observed empirical moments.*

	ρ	θ	σ^2_α	σ^2_ϵ	σ^2_ξ	Prop. Perm	MSE
Less than HS strict	0.375***	-0.121***	0.164***	0.360***	0.348***	0.279	0.049
	(0.002)	(0.000)	(0.000)	(0.003)	(0.006)	(0.009)	
Less than HS lenient	0.353***	-0.102***	0.274***	0.878***	0.877***	0.232	0.017
	(0.006)	(0.001)	(0.002)	(0.018)	(0.019)	(0.009)	
High School strict	0.350***	-0.042***	0.146***	0.356***	0.306***	0.255	0.035
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	
High School lenient	0.352***	-0.059***	0.211***	0.728***	0.636***	0.234	0.008
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)	
Some College strict	0.357***	-0.040***	0.148***	0.292***	0.246***	0.267	0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	
Some College lenient	0.353***	-0.072***	0.184***	0.604***	0.498***	0.246	0.008
	(0.001)	(0.000)	(0.000)	(0.004)	(0.003)	(0.017)	
College strict	0.344***	0.084***	0.138***	0.320***	0.321***	0.227	0.007
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.006)	
College lenient	0.367***	0.022 ***	0.208***	0.555***	0.540***	0.240	0.012
	(0.001)	(0.000)	(0.000)	(0.005)	(0.005)	(0.021)	

Table 3: Results core parameters for Female Samples.

Note: $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$. *All hypothesis tests are two-sided. Standard errors are presented in brackets beneath parameter estimates. Prop. Perm measures the mean ratio between predicted permanent variance and the sum of predicted permanent- and transitory variances. MSE is mean squared error between predicted and observed empirical moments.*

historical shocks have on expected future earnings. Since all estimates are positive, one can interpret it in terms of what proportion of historical shocks is expected to persist in the next period. An AR(1) parameter of 0.5 implies that transitory shocks to earnings linger between periods and accumulates, but the effect of each shock is decaying and is expected to be halved each year. These findings suggest that a relatively short longevity of shocks to earnings among Swedish workers. Relating our estimates to Gustavsson (2007, 2008), transitory shocks seem to have become less persistent over the time horizon of 1960-2015. It is however important to note the difference in profile specification between the models, given the exclusion of a unit root in our model.

The estimates for the MA(1) process are less systematic, depending on the sample the MA(1) parameter can be negative or positive. Most estimates are relatively small in absolute value, the largest being -0.121 estimated for the strict sample for females with less than high school education. In the female samples, the estimates for the all education groups exempt the college educated are negative. When it comes to the variance of the ARMA(1,1) shocks, then there is a clear difference between the males and females regarding the estimates. The estimates for the female samples are larger than those for their male counterparts. Another pattern is visible when comparing the strict and the lenient selections. The variance of the ARMA(1,1) process is larger for the lenient selection. This can partly be explained by the truncation of the earnings distribution in the strict samples. The restriction to only consider those relatively well established on the labor market in the strict sample provide another plausible explanation.

Analyzing the estimated variances for the initial shocks upon entering the labor market σ_ξ^2 one find that these are significantly larger for the lenient selection when compared to their strict counterparts. This can also be explained by potential selection effects. For the male samples then the initial shock is systematically larger than the variance of the ARMA(1,1) shock. This could be interpreted as the earnings for initial year on the labor market being more volatile than subsequent years. The same pattern was however not observed for females.

6.2 Permanent and transitory variability

The share of variance in earnings attributable to permanent relative to transitory variance (*Prop. Perm* in table 2 and 3) is of interest because of its policy implications. In order to compare the relative contribution of the permanent and transitory components to overall earnings variability we predicted how much of the overall variance is attributable to the permanent component based on all parameter estimates. This measure is labeled as *Prop. Perm* in Table 2 and 3.

For all samples, the estimated permanent component contributes less to the overall variability of earnings than its transitory counterpart. The largest proportion was found among college educated men in the strict selection. In this group 42.1% of overall variability of earnings is estimated to be attributable to permanent variance. The smallest proportion was found among females with college education in the strict selection. This group had a 22.7% proportion of overall variability that was attributable to permanent differences. Comparing the estimates for men and women one finds that the relative importance of the permanent variance seem to be higher among men. This could possibly be a result of higher variability in the supply of labor among women. The proportion of overall variability attributable to the permanent inequality is lower in the lenient samples. This result was expected as these samples include additional individuals that are less established on the labor market. The difference between the strict and lenient samples is however larger for men than for women.

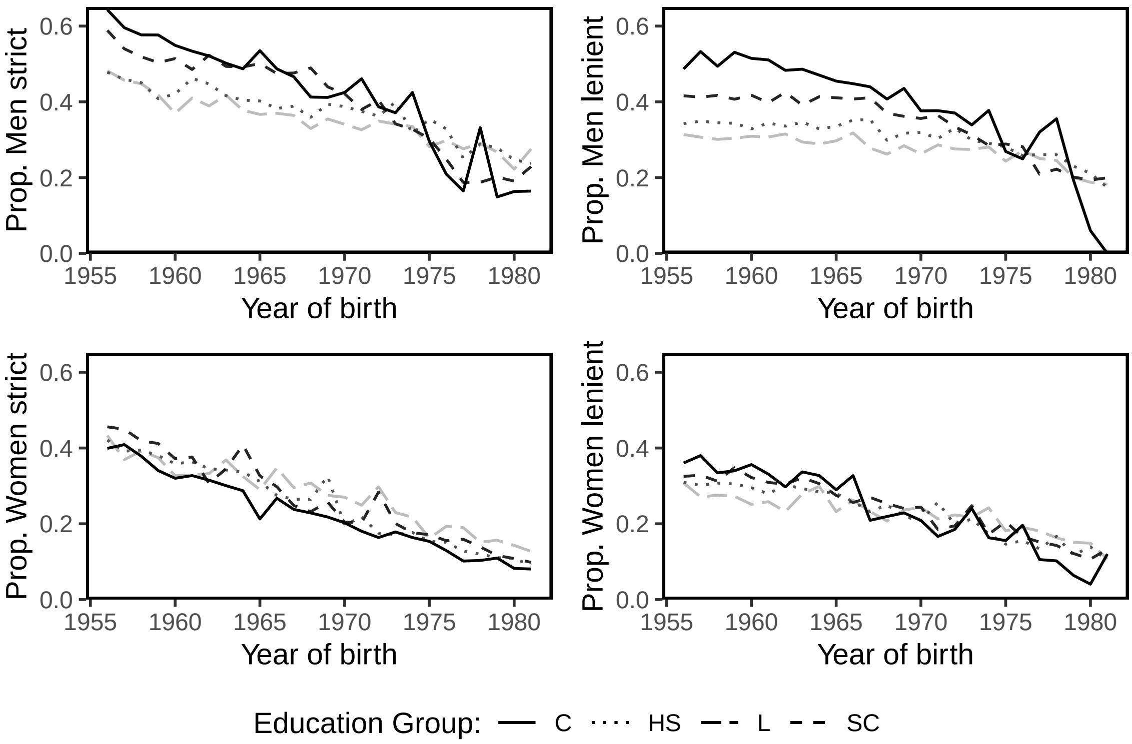

Figure 4: Proportion of overall variance in earnings attributable to permanent inequality.
Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

If one decomposes the proportion of overall variance in earnings attributable to permanent differences by birth year cohort one find a difference between the older and younger cohorts, where the younger cohorts have a higher proportion of transitory variability than their older counterparts. This is consistent with younger workers being more mobile on the labor market. The largest differences between cohorts can be found for the more educated workers in the male samples.

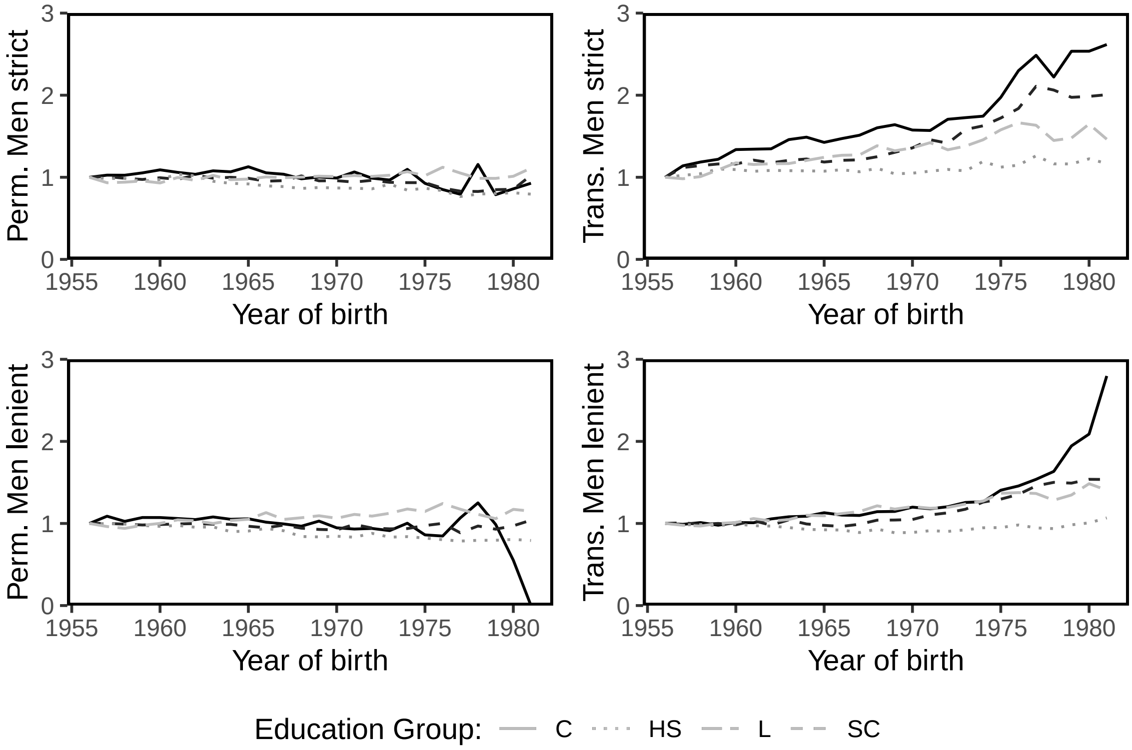

Figure 5: Cohort factor loadings Male Samples.
Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

6.3 Factor loadings

By analyzing the factors loadings it is possible to see how the decomposition of inequality differs between younger and older cohorts, and how the proportions of permanent and transitory inequality have changed over the observed time period of 2002-2015. The cohort factor loadings describe the size of the permanent- or transitory variance and autocovariances of a specific cohort subsample in relation to the groups born 1956. The time factor loadings describes the relative size of the permanent- and transitory variance and autocovariances for a specific year with 2002 as the reference.

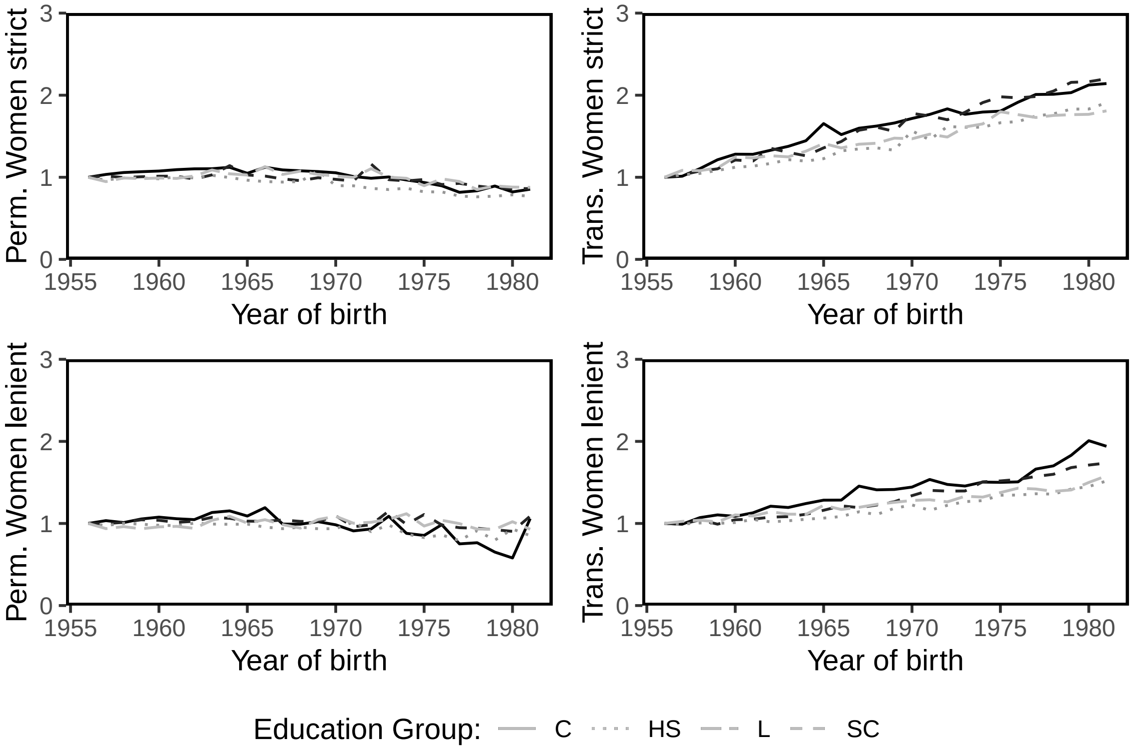

Figure 6: Cohort factor loadings Female Samples.
Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

Concerning cohort factor loadings, both the strict and lenient samples indicate that that younger cohorts have relatively more volatile earnings than older cohorts. This is true for both male and female samples and can be considered intuitive since younger workers are expected to be more mobile between work places, partially induced by hiring/firing restrictions, and by frictional unemployment due to a higher tendency for younger individuals to voluntarily switch job places. The timing of labor market entry with respect to the financial crisis could potentially contribute to this, as the unemployment risk for young workers increased more relative to other groups during the financial crisis (Statistics Sweden, 2014). This could potentially be explained within the institutional setting of the employment protection act which regulates firms to follow a last hired - first fired principle. Since we are unable to control for hours worked, we should also expect the presence of individuals working part-time to financially support their educational commitments to inflate the estimates of earnings volatility among younger workers. This finding is further supported by Björklund (1993) who concludes that the correlation between annual income and life-time income is lower for younger workers than for older workers.

While both female and male samples are characterized by transitory factor loadings increasing for the younger cohorts, there are differences worth noting. For females, the increase is almost linear as revealed by both strict and lenient samples and the different educational groups follow similar patterns. From Figure 5 and 6, one can see that the smaller contribution of permanent inequality to the overall earnings inequality for the younger cohorts, as seen in Figure 4, can to a large extent be explained by higher levels of transitory inequality for these groups. For the strict male sample of college graduates, the increase is seemingly linear for birth cohorts 1956-1972, convex for birth cohorts 1973-1977, and seem to remain at a higher level for birth cohorts 1978-1981. Regarding the increase for individuals with less than high school education, the evolution is initially similar to the one observed for college graduates with a less dramatic increase for the younger cohorts. The change in transitory inequality is smallest for high school graduates. The high transitory inequality observed for male college graduates could be explained by the fact that it is common to enter the labor market before graduating from college. The earnings that we observe for the younger cohorts with college education could therefor include individuals working part time to a greater extent than within other education groups that have graduated before the age of 25. Differences in transitory inequality between educational groups for female cohorts are not as pronounced, although the change in transitory inequality between cohorts have been largest for the college educated groups.

Regarding the permanent cohort factor loadings for women, the increase in transitory inequality for the youngest cohorts have to some extent been mirrored by a decrease in the factor loadings for the permanent variance. This could be either trends in the nature of income inequality between cohorts or a result of weak identification when simultaneously estimating both permanent and transitory factor loadings. The estimates are more volatile in the lenient data, where the permanent factor loading for college educated women born 1980 provide an example of an outlier.

The increase in the transitory variance for males is less systematic and there is no clear downward trend in the permanent factor loadings. For the college educated and individuals without high school education in the strict sample the transitory factor loadings increases relatively slowly for cohorts born between 1956-1972. After that the transitory factor loadings start to increase rapidly for the college educated peaking for those born 1977. For the high school educated the evolution of the factor loadings is less dramatic, it is larger for the younger cohorts but the difference is not as large as for the other education groups. In the lenient data then the trends for the transitory variances are less clear. For individuals with less than a high school degree and the college educated the factor loadings increase for the younger cohorts, much like the other samples. During the latter part of the 1970s there is a large increase in transitory variance for the college educated, similar to that found in the strict sample but smoother. However, for the high school educated the transitory variance is initially decreasing and cohorts up till those born 1976 have smaller factor loadings than the 1956 cohort.

In the strict sample for men, the permanent factor loadings are relatively stable, especially among the college educated and those without high school education born between 1956-1974. After that there is a general decrease for both groups, although for the college educated there is a rebound in 1978. For the high school educated one see a relatively steady downward trend similar to that found for the females. In the lenient sample the high school educated follow a relatively stable pattern similar to that found in the strict sample and the individuals with less than high school education the factor loadings fluctuate around 1 without any clear trend. The permanent factor loadings for the college educated are relatively stable for cohorts born between 1956 - 1978, after that there is a sharp almost linear decline for the remaining cohorts.

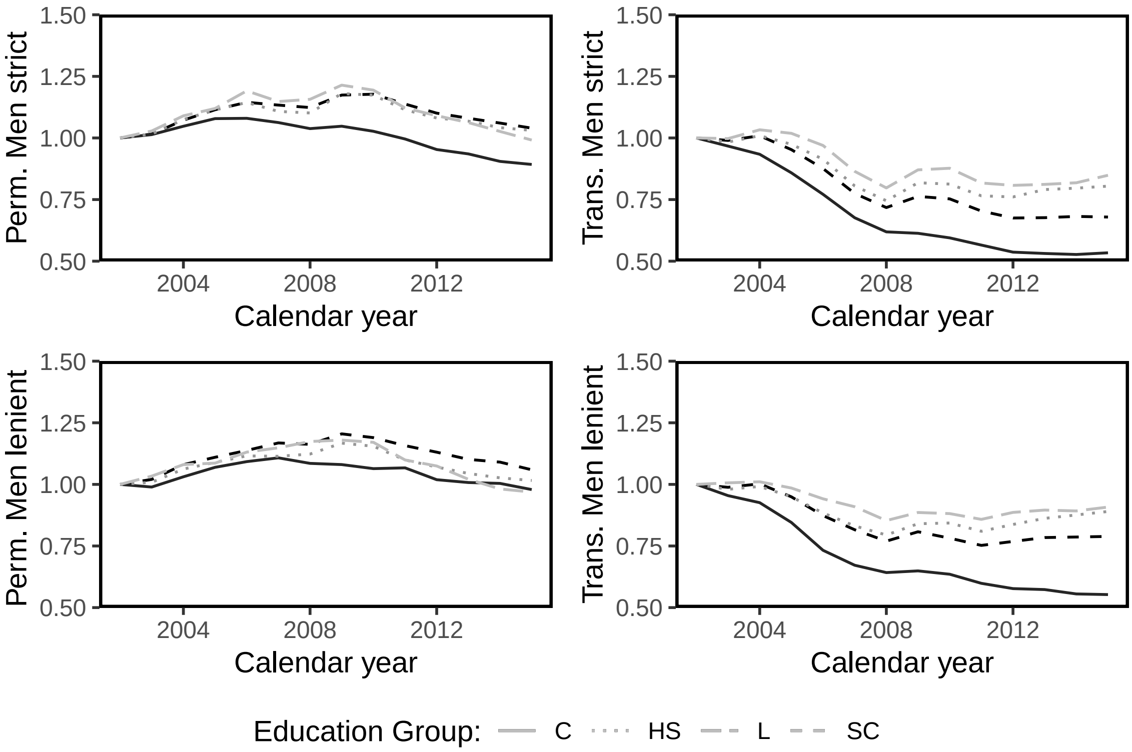

Figure 7: Time factor loadings Male Samples.

Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

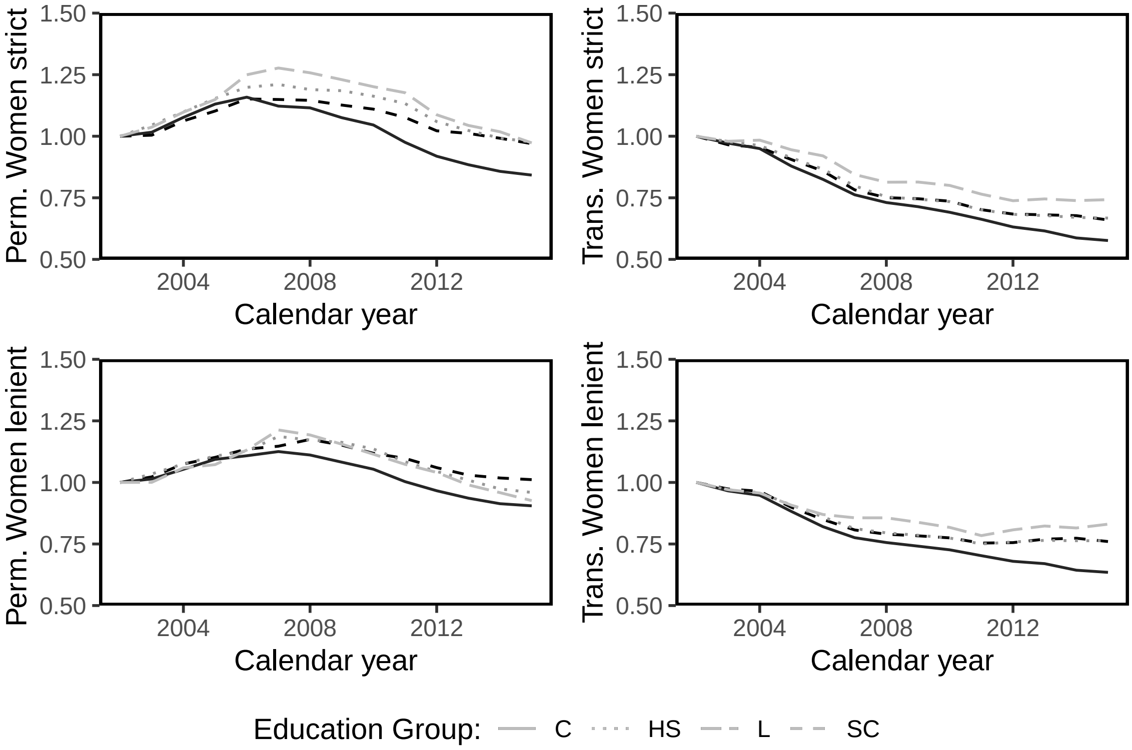

Figure 8: Time factor loadings Female Samples.
Note: Education groups are: Less than high school (L), high school (HS), some college (SC) and college (C).

For the time factors presented in Figure 6 and 7 one of the most striking features is the small impact from the 2008 financial crisis on the volatility of earnings. There is a small increase in the permanent and transitory variability for the less than high school and high school educated males, most prominently in the strict sample, while the crisis had no apparent impact on the volatility of female earnings. The financial crisis of 2008 mainly affected Swedish exports, and one could hypothesize that employment in the protected public sector implies less earnings risk in times of economic recession, explaining the results for females. The trends and changes in values at the time of the crisis is smaller in the lenient sample, when compared to the strict. This could possibly be an effect of higher rates of long-term unemployment (more than a year) in these samples.

7 Simulation of Income pension entitlements

The Swedish public pension underwent a major structural transition in the 1990's from a defined benefit plan, to a combined pay-as-you-go notional defined contribution (income pension), financial defined contribution (premium pension), and defined benefit scheme (guaranteed pension). The reform implied that a larger risk for ensuing sufficient individual pension funds is now placed on people themselves. Entitled annuities are to a greater extent decided by life-time income rather than weighted from top income years, as with the old system (Palmer et al., 2000). We limit our application to only encompass features of the income pension scheme.

As with any notional defined contribution plan, individual contributions are registered as future entitlements rather than money being deposited into an actual fund. Payments are instead used to support solvency for withdrawn benefits. Each year, the individual receives a balance statement of entitlements and a projection of future pension wealth based on earnings history. The earnings profile will subsequently be a central feature in any prediction of future pension entitlements for individuals. Related to model specification, the conventional RIP process would assume the variability of pension contributions to increase linearly over the life-cycle, while a stationary process as found evidence for in this process would imply a cohort-specific constant contribution variability adjusted by year factors.

Furthermore, earnings extrapolations are of importance not only for individual projections, but also for forecasting financial solvency on the aggregate. This would be a suggested topic for future studies, given the lingering challenges for welfare states associated with balancing accounts as longevity increases and fertility rates declines. Since we only analyze earnings and omit other income sources such as capital income and transfers, we limit this application to an approximation of individual entitlements and the sample distributions.

7.1 Simulation procedure

Simulations are conducted for each gender and education group sub-sample of both the lenient and strict selection used to estimate the life-cycle model of earnings. For each sub-sample, 10000 simulations are conducted. Individuals are assumed to register their first labor income at age 25, full-time retire at the age of 65, without the possibility to re-enter the labor market post-retirement. We assume no partial withdrawals of funds prior to the age of 65. Death is assumed to be inflicted with certainty, and we set the longevity parameter to correspond to the cohort-specific life expectancy after the age of 65. We calculate life expectancy as the average of male and female life expectancy to emulate the gender neutrality of the annuitization divisor utilized by the Pension agency. Our birth cohort span of 1956-1981 only includes cohorts fully integrated into the post-reform scheme.

Since our simulations only concern earnings, the contributions to the pension account balance are entirely derived from individual life-time earnings. Pensionable income is proxied by 93 percent of simulated earnings, for which a fixed rate of either 0.185 (for income registered prior to 1995) or 0.16 is allocated to the individual pension account balance. For years in retirement, the pension account balance is divided by the number of years in retirement and registered as annuities. Since pensionable income is not relegated to earnings only, but also capital gains and various transfers, this is a simplification of the true pension fund accumulation process. Furthermore, any innovations are assumed normally distributed.

Pensionable income is further limited to amounts qualifying as taxable income (43.2 % of the price base amount), and can not surpass 7.5 times the income base amount. As of now, we extrapolate the price base amount and income base amount to proportionally follow the evolution of projected GDP/capita growth. This subsequently truncates extreme contributions to the notional accounts.

Given the high degree of uncertainty involved in long-run forecasts of the macro environment it is common in micro-simulations to use static assumptions regarding macroeconomic variables. With our aim being to model entitlements, and not aggregate financial solvency, we deem a simple macroeconomic scenario as adequate in line with (Moore and Mitchell, 1997). Rather than purely stylized values for economic growth, we assume growth to follow the projections of MIMER[19] (see table 1), a general equilibrium model with overlapping generations employed by the Swedish ministry of Finance (Finansdepartementet). While MIMER does not explicitly account for business cycle fluctuations, it integrates demographics change which is commonly used as a predictor for business cycle fluctuations as in Röstberg et al. (2005). To project yearly mean earnings beyond our observed time period, we conduct an OLS regression of yearly mean earnings on GDP/capita, education dummies and cohort dummies.

[19]For a detailed description of MIMER, see Almerud (2018).

1980-2013	2014-2024	2025-2034	2035-2044	2045-2060
1.7	1.6	1.5	1.8	1.8

Table 4: Historical and forecasted average annual GDP per capita growth (%)

7.2 Simulation results

Given the extensive number of simulations conducted, we present a selection of results. Figure 9 depicts the simulated distributions of the first pension entitlement for each education group of both male and female gender born in 1970, given estimates from the strict selection.

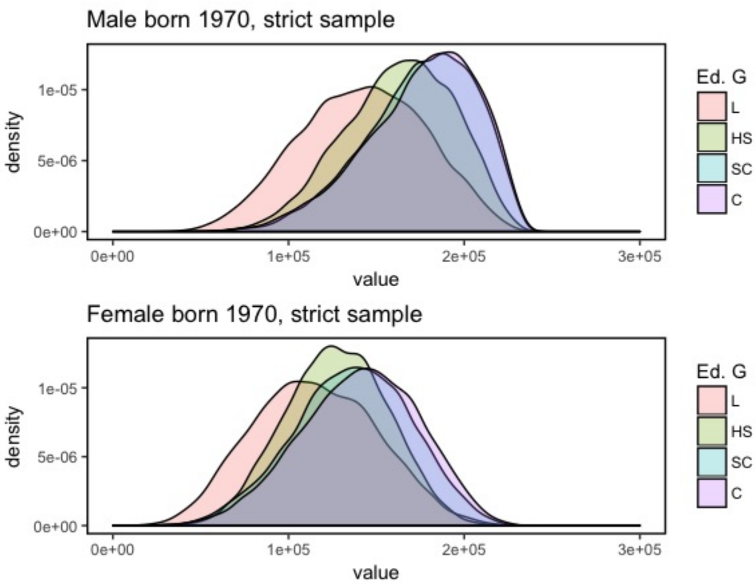

Figure 9: Distribution of male and female pension entitlements over education groups (birth cohort 1970)
Note: Education groups (Ed.G) are: Less than high school (L), high school (HS), some college (SC) and college (C).

Pension entitlements of both college groups are more evidently subjects of the truncation due to the upper limits of contribution amounts, ultimately reducing the overall variability of pension entitlements. The population with less than high school education displays relatively higher within-group variability compared to both high school educated and both college groups probably due to fewer recorded earnings higher than the upper limit amount for pensionable income.

The pension entitlements for females over education group follow the same overall pattern as the male counterpart with generally higher entitlements for higher educational attainment. However, it is interesting to note that the female college groups are not visibly as bound by the upper limit to pensionable income as the male college groups. Ultimately, the within education group-variability is less dispersed compared to the male groups.

7.3 Sensitivity

We illustrate the role of the permanent-transitory framework in predicting the distributions of pension entitlements by varying the parameters as isolated events. Figure 10 illustrates how the distribution of pension entitlements vary with the AR-parameter and the MA-parameter respectively.

One would expect that changing any of the ARMA parameters would not affect the distribution, conditional on that the model remains stationary and innovations are normally distributed and of moderate persistence. This is confirmed by our analysis. However, when the AR-parameter approaches unity and shocks tend to maximum persistence, the distribution of pension entitlements become less dense around the mean and eventually collapses into two distinct humps indicating a substantial polarization of entitlements. It is likely that these humps are a product of truncation due to the limits of pensionable income.

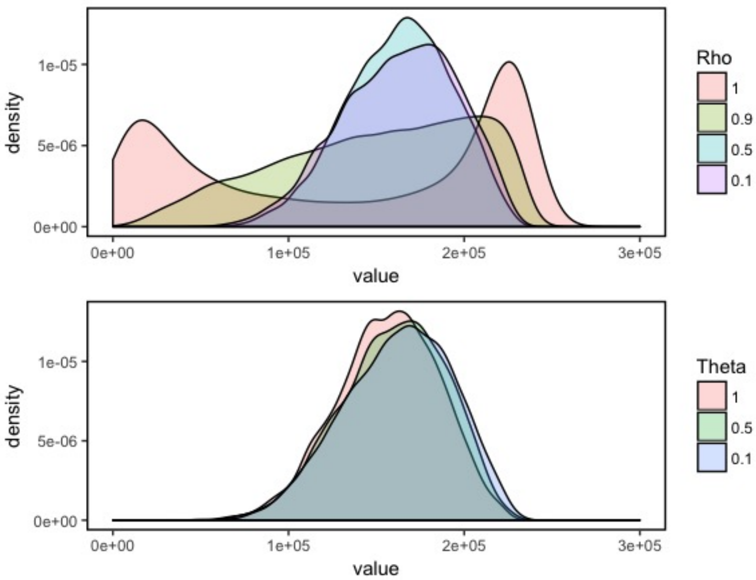

Figure 10: ARMA parameters
Note: Rho = AR-parameter, Theta = MA-parameter. Baseline parameterization follows from the strict selected male sample of the 1970 birth cohort. 10000 simulations were conducted for each parameterization.

Since pension entitlements are derived from life-time earnings, it is expected that the life-cycle profile will contribute more relative to transitory earnings fluctuations in determining the distribution of entitlements. Figure 11 illustrates how variations in the variance of the earnings profile and the variance of the earnings shock affects the distribution.

An interesting finding is that while an increased permanent variability implies a wider distribution of pension entitlements, an increased transitory variability contracts the distribution. It could be possible that the explanation for this peculiarity lies within the truncation of pensionable income: With larger variability of earning shocks, individuals with low initial earnings might experience positive enough earnings shocks which renders their income as qualifiable as pensionable income on a more frequent basis than if the variability of transitory shocks is small.

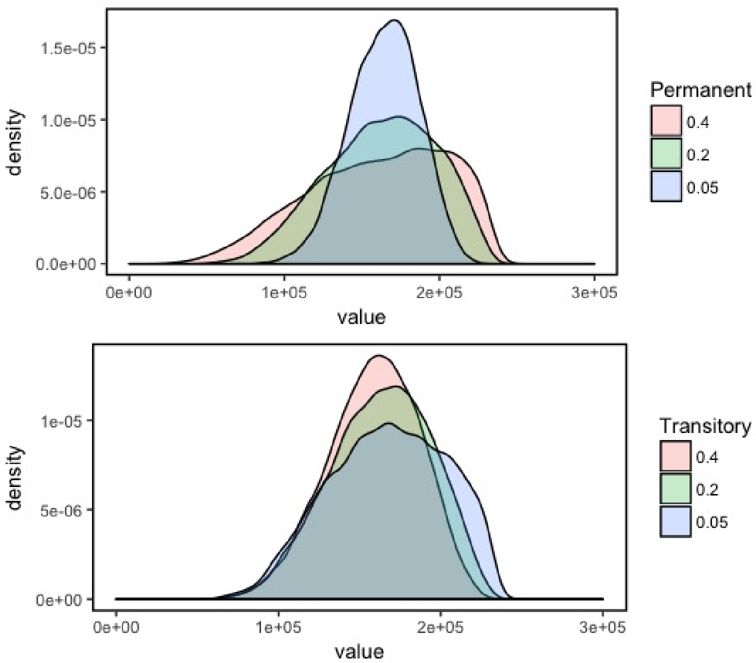

Figure 11: Variance of the earnings profile and the transitory shock
Note: Baseline parameterization follows from the strict selected male sample of the 1970 birth cohort. 10000 simulations were conducted for each parameterization.

Overall, the variability of the permanent component is found to be the largest contributing source to the distribution of pension entitlements. However, given the surprising finding that transitory inequality contributes to contract the distribution of pension entitlements, it's omission could lead to an overestimation of pension inequality. As long as the model is stationary with moderate persistence, the ARMA parameters does not clearly affect the distribution.

8 Conclusions

We have analyzed annual earnings for people born between 1956-1981 in Sweden during the years 2002-2015. The goal was to assess to what extent variations in earnings can be attributed to long term differences between individuals contra short term instabilities. Analyzing different educational groups, both men and women, and partially controlling for selection effects we aspired to characterize earnings dynamics in Sweden.

Comparing the relative sizes of the transitory and permanent variances we found that the variance of the transitory component was substantially larger than its permanent counterpart. Furthermore, we found larger permanent variances among the higher educated males and less educated females. In turn, this information is relevant for the design of policies aiming to counteract high variability in earnings. If the shocks are of a transitory nature then social insurances, such unemployment benefits, could provide adequate policy instruments. Counteracting variance in earnings of a more persistent or permanent nature would require other policy actions, such as redistribution via the tax system.

Another interesting finding was the similarities in the dynamics of the earnings process found between education groups and gender. Even though the parameter estimates differ between the regressions, the general patterns are strikingly similar. The largest variations are found for the estimates of the variance of the ARMA(1,1) process.

The traditional HIP and RIP specification of the permanent income does not in our view provide an obvious fit to the Swedish data. One of the most striking features found in our data were declining, or at the very least not increasing, variances in earnings over the life-cycle. Although the model used is parsimonious, it manages to explain the patters found in the data relatively well and yields estimates that are consistent across different education groups, sample selection criteria and genders[20].

One can argue that the model could be complemented with additional variables, especially a more comprehensive trend, but these augmentations might have to look beyond the traditional HIP/RIP framework. A possible extension to the model would be to add a component allowing for a decrease in the permanent variance over the life cycle as well or include variables for the short and long term effects of general versus vocational education. Another approach would be to model transitions in and out of employment, allowing for the effects of long term unemployment to contribute to the earnings dispersion. Further research is needed for better understanding of the earnings process of the Swedish labor market; for instance by estimating a more structural model including factors such as transitions between employment and unemployment.

The role of human capital accumulation in the within-group variation

[20] Plots for regression fit and residual distribution can be found in Appendix D, figures 28-31

of earnings over the life-cycle is not obvious in our analysis. The compression of earnings over the carrier observed cannot be explained solely by a Mincerian-crossover effect. A possible explanation could be the Swedish wage bargaining model limiting wage dispersion within groups (Edin and Topel, 1997). The variability of earnings could be driven by the variation in hours worked, where the younger individuals could be more likely to have part-time employments and therefore more volatile working hours than older better established workers. This could potentially counteract and dominate any wage effect of human capital accumulation. While the evolution of permanent earnings inequality observed during the 1990's has been ascribed an increase in skill prices Gustavsson (2007), it could be questioned whether this has continued given our findings that permanent earnings inequality has not increased of any substantial magnitude.

From simulations of income pension entitlements, we find that the within-group variability of college educated is lower relative to less educated groups. We conclude this to follow from higher educated individuals being more frequently bound by the the upper limits of pensionable income. This holds true for both males and females, but the within education group-variability is less dispersed for females compared to males. From a sensitivity analysis we conclude the variability of the earnings profile to be the major contributor to overall pension inequality, but also that earnings risk has a contracting effect on the distribution of entitlements which motivates its inclusion when forecasting pension entitlements.

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Appendix: Earnings dynamics in Sweden

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May 2019

Appendix

Appendix A: Empirical variance and fist three covariances by gender and filter

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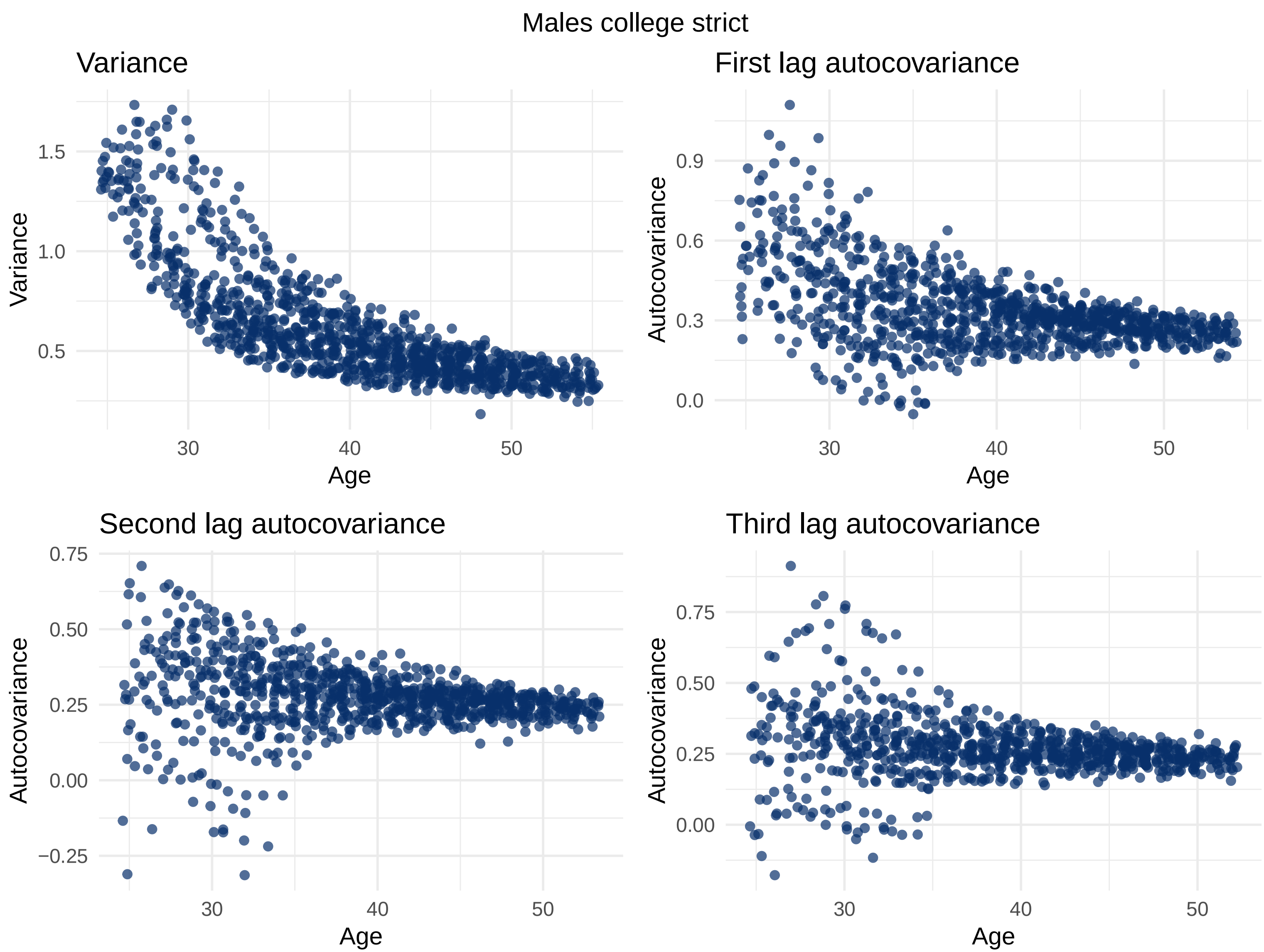

Figure 1: Variance and first three autocovariances of log earnings for males college strict.

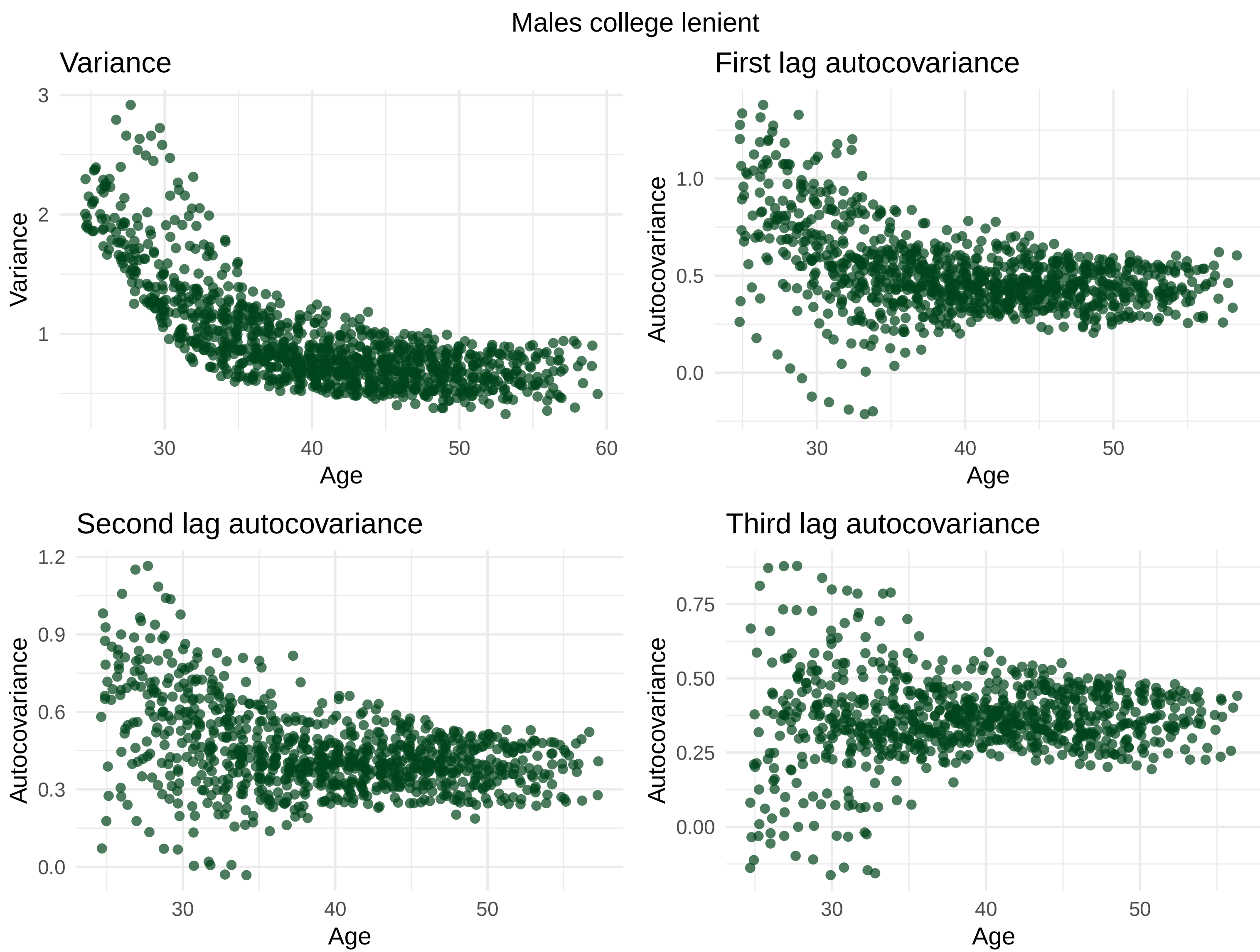

Figure 2: Variance and first three autocovariances of log earnings for males college lenient

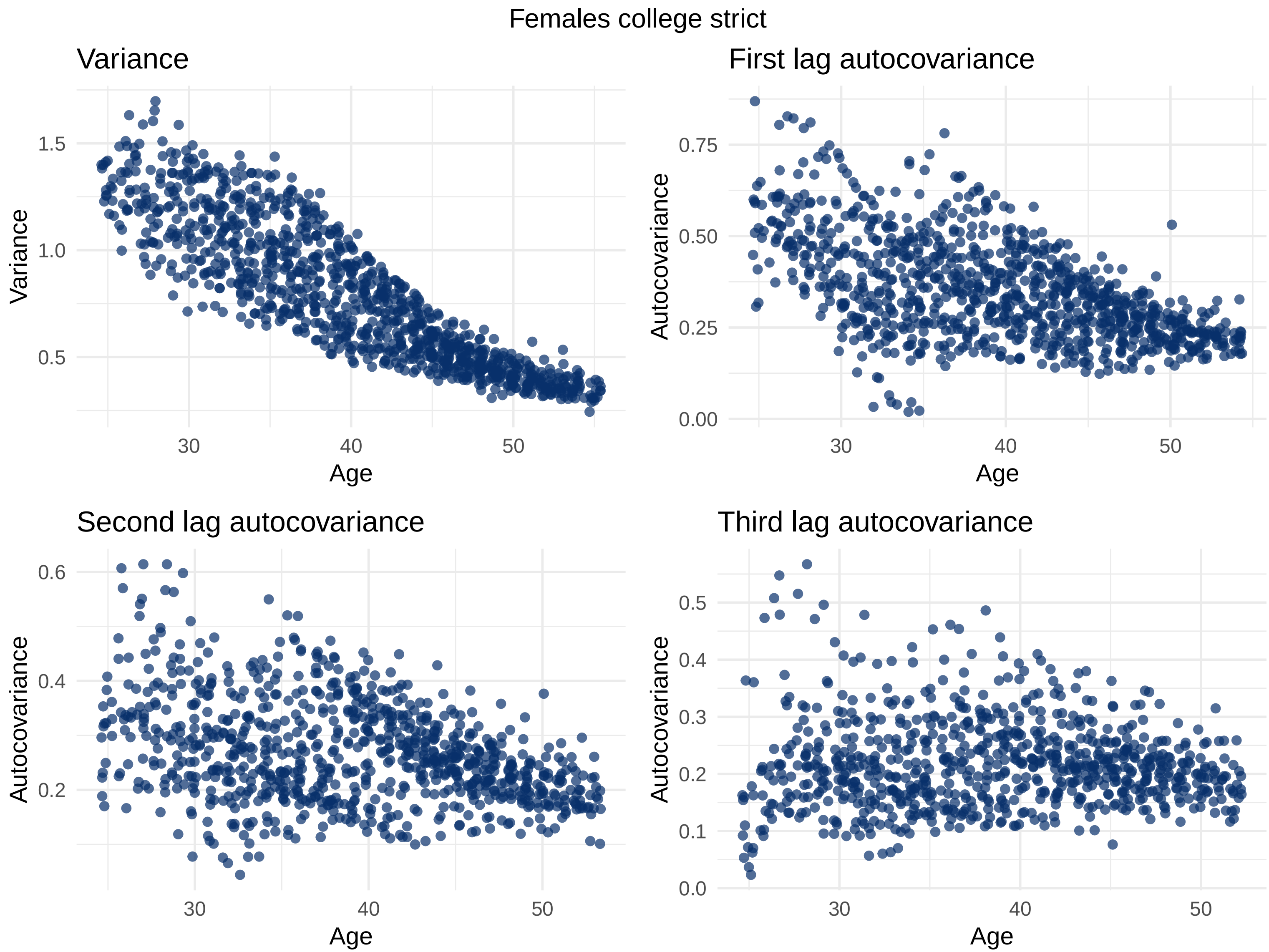

Figure 3: Variance and first three autocovariances of log earnings for females college strict.

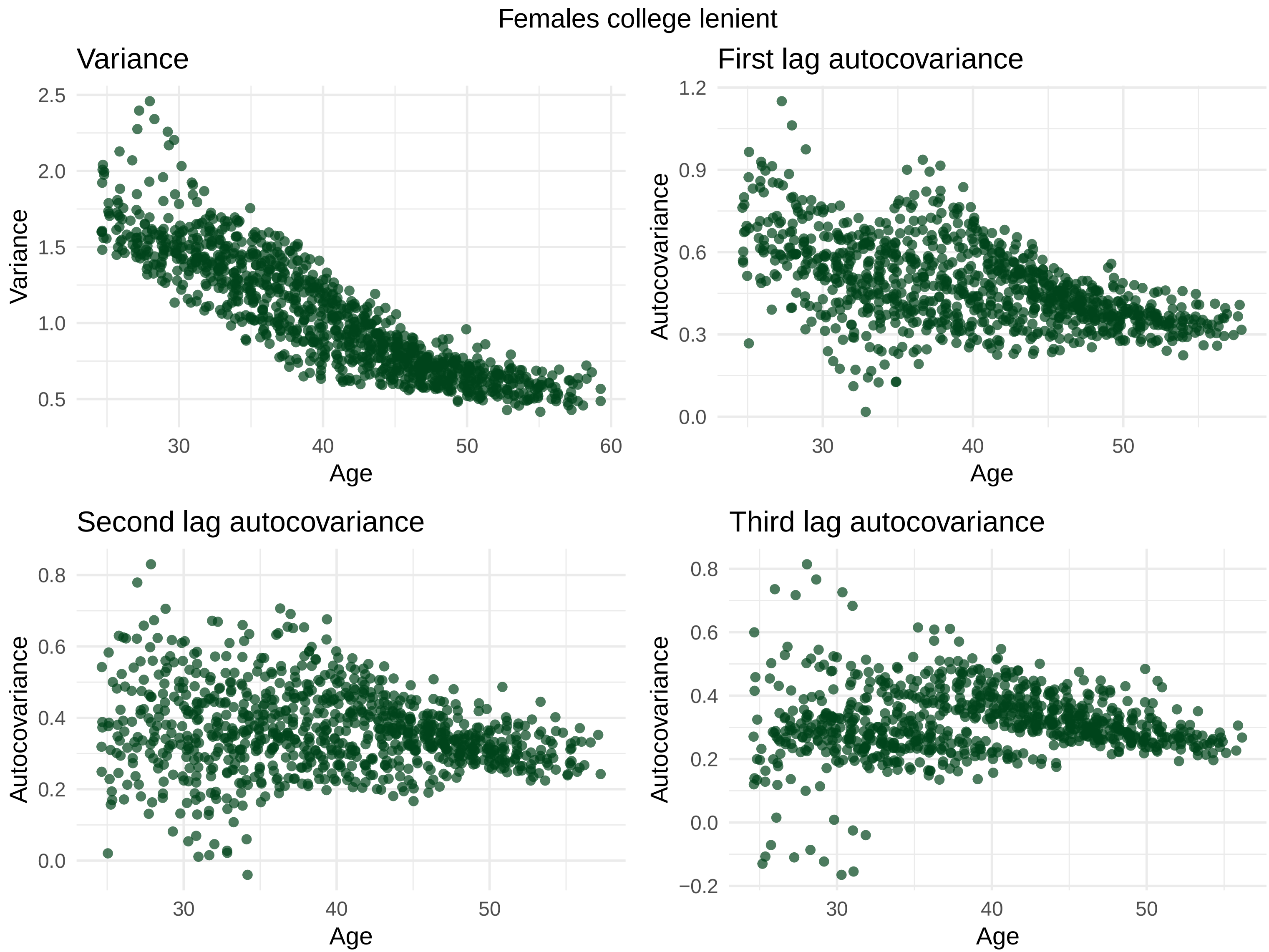

Figure 4: Variance and first three autocovariances of log earnings for females college lenient.

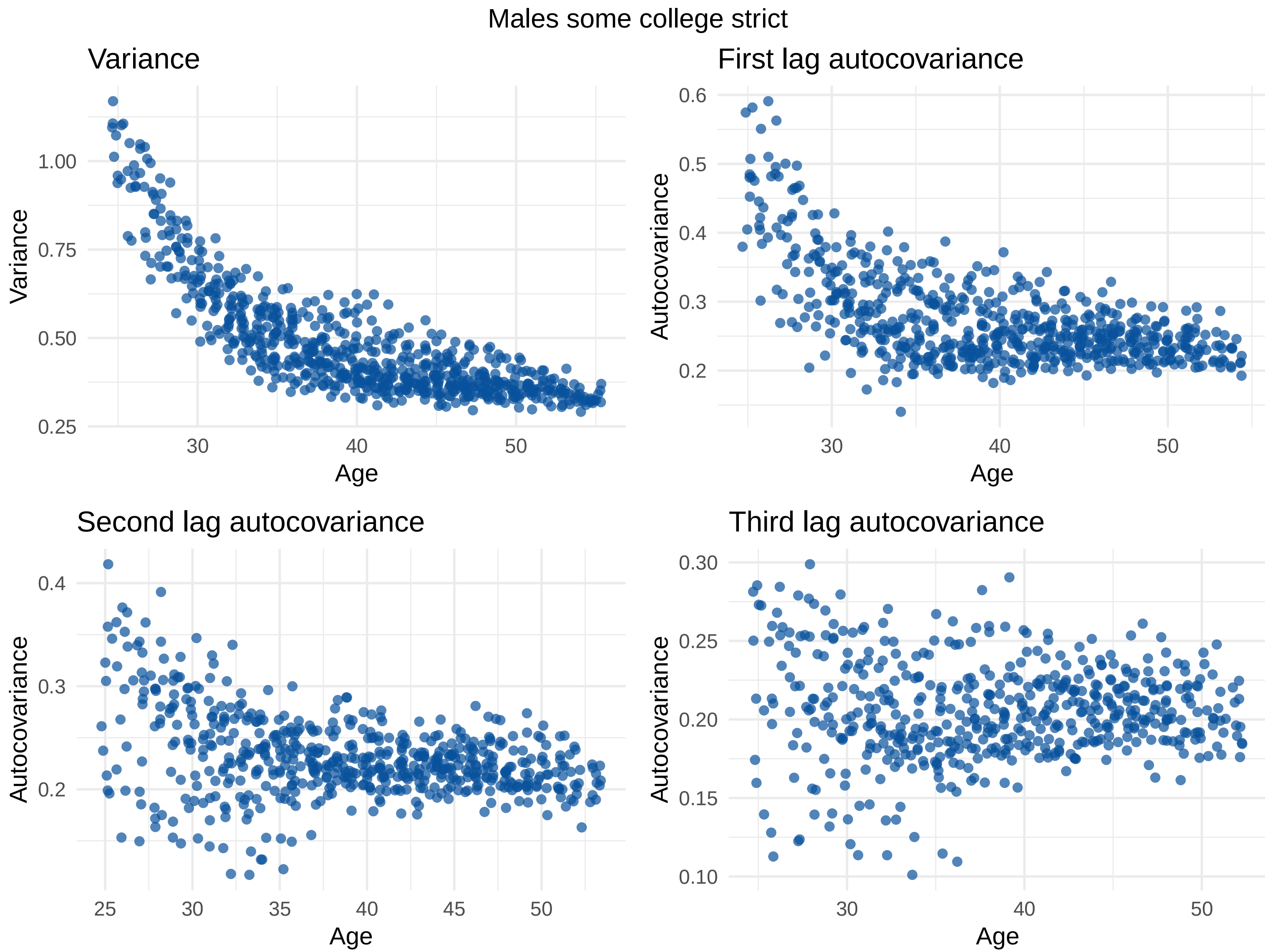

Figure 5: Variance and first three autocovariances of log earnings for males some college strict.

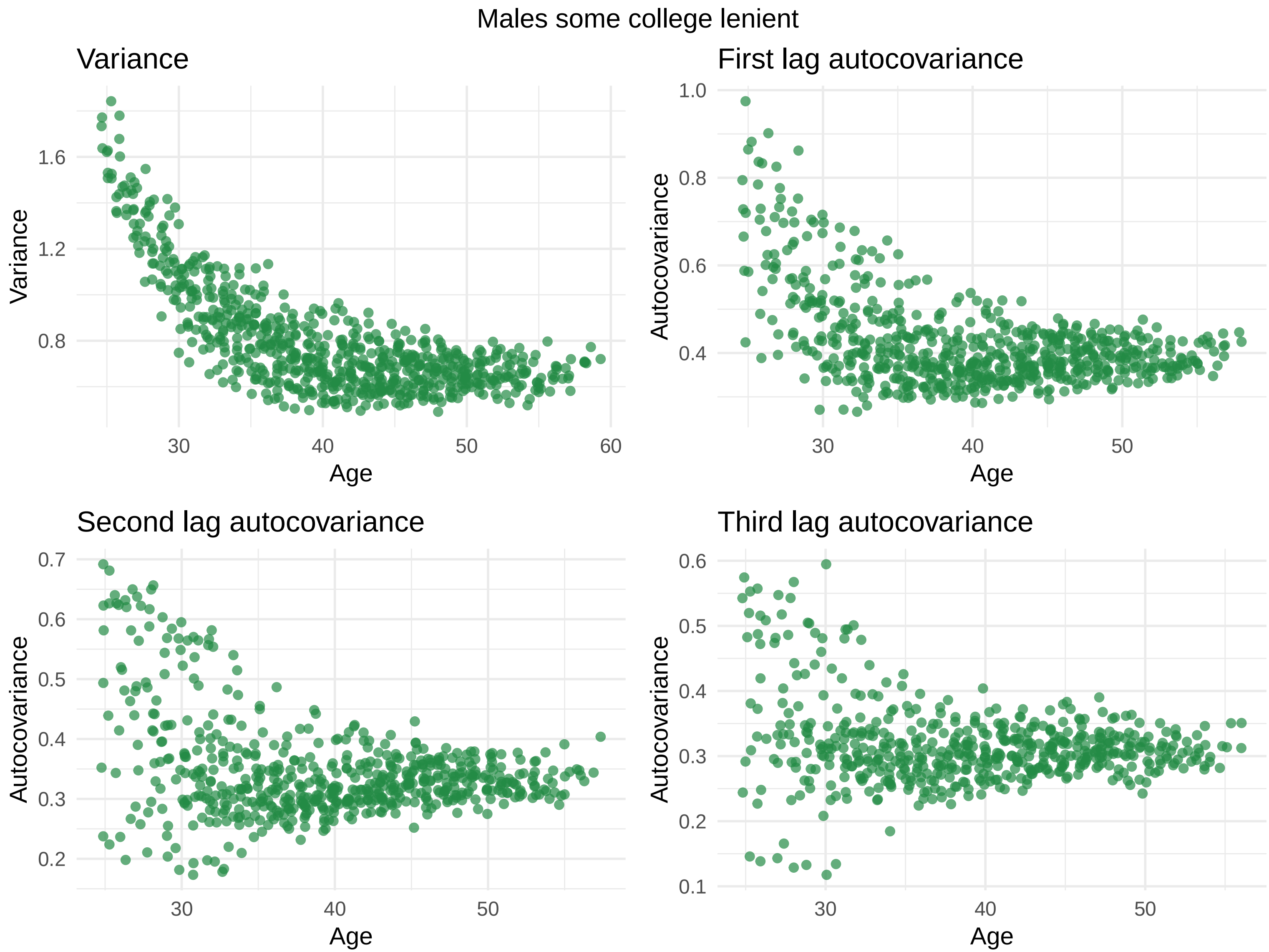

Figure 6: Variance and first three autocovariances of log earnings for males some college lenient.

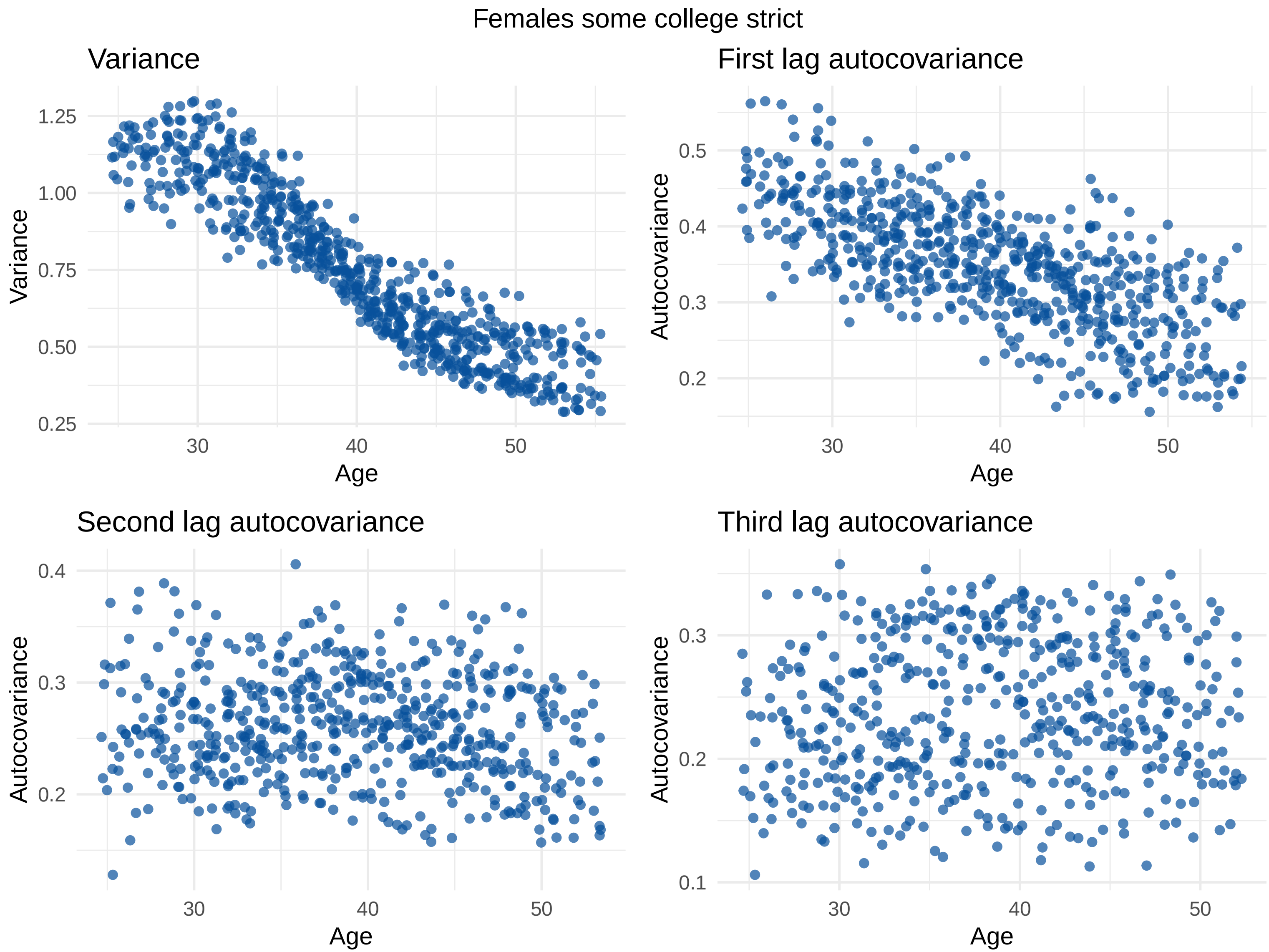

Figure 7: Variance and first three autocovariances of log earnings for females some college strict.

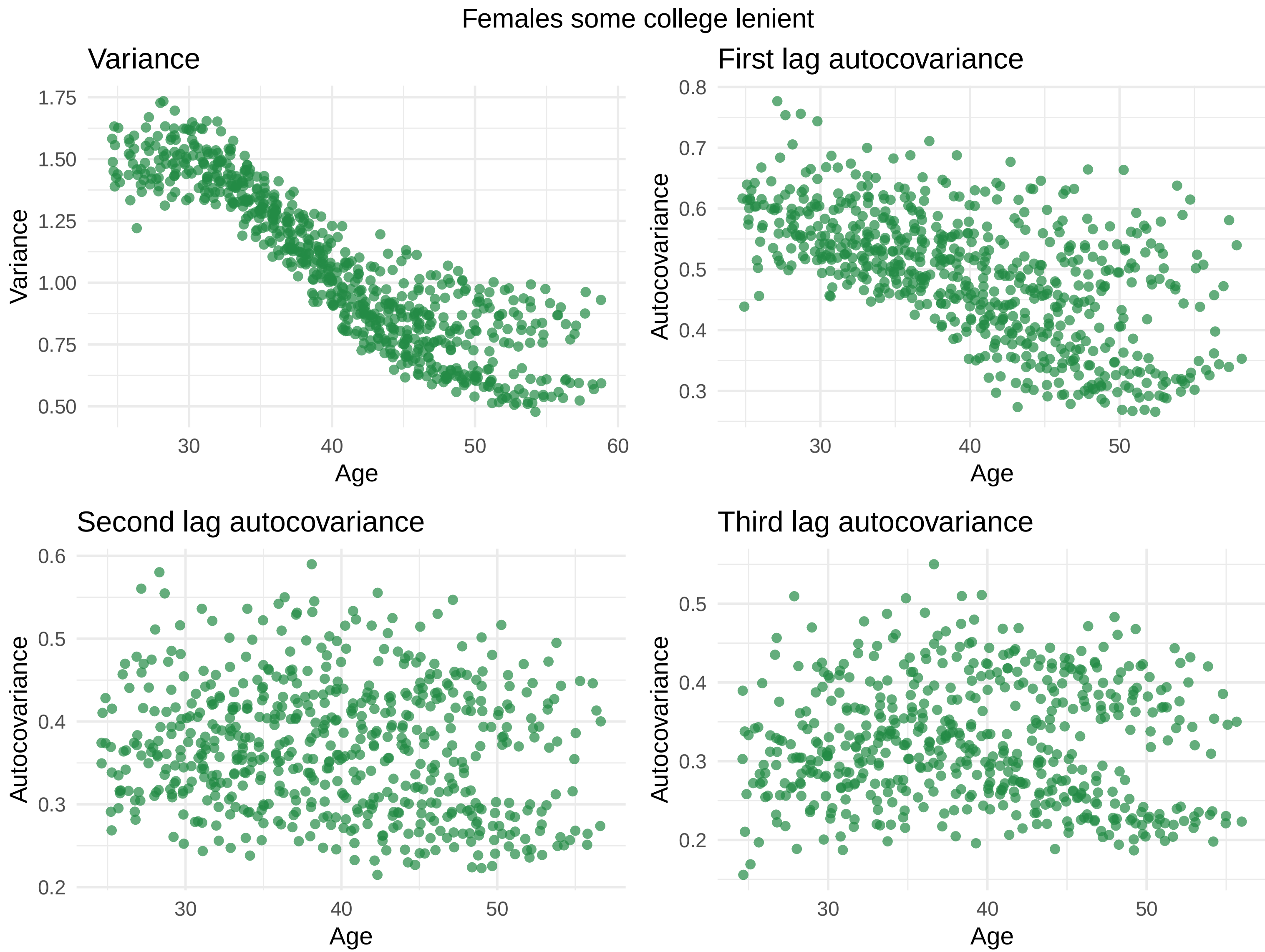

Figure 8: Variance and first three autocovariances of log earnings for females some college lenient.

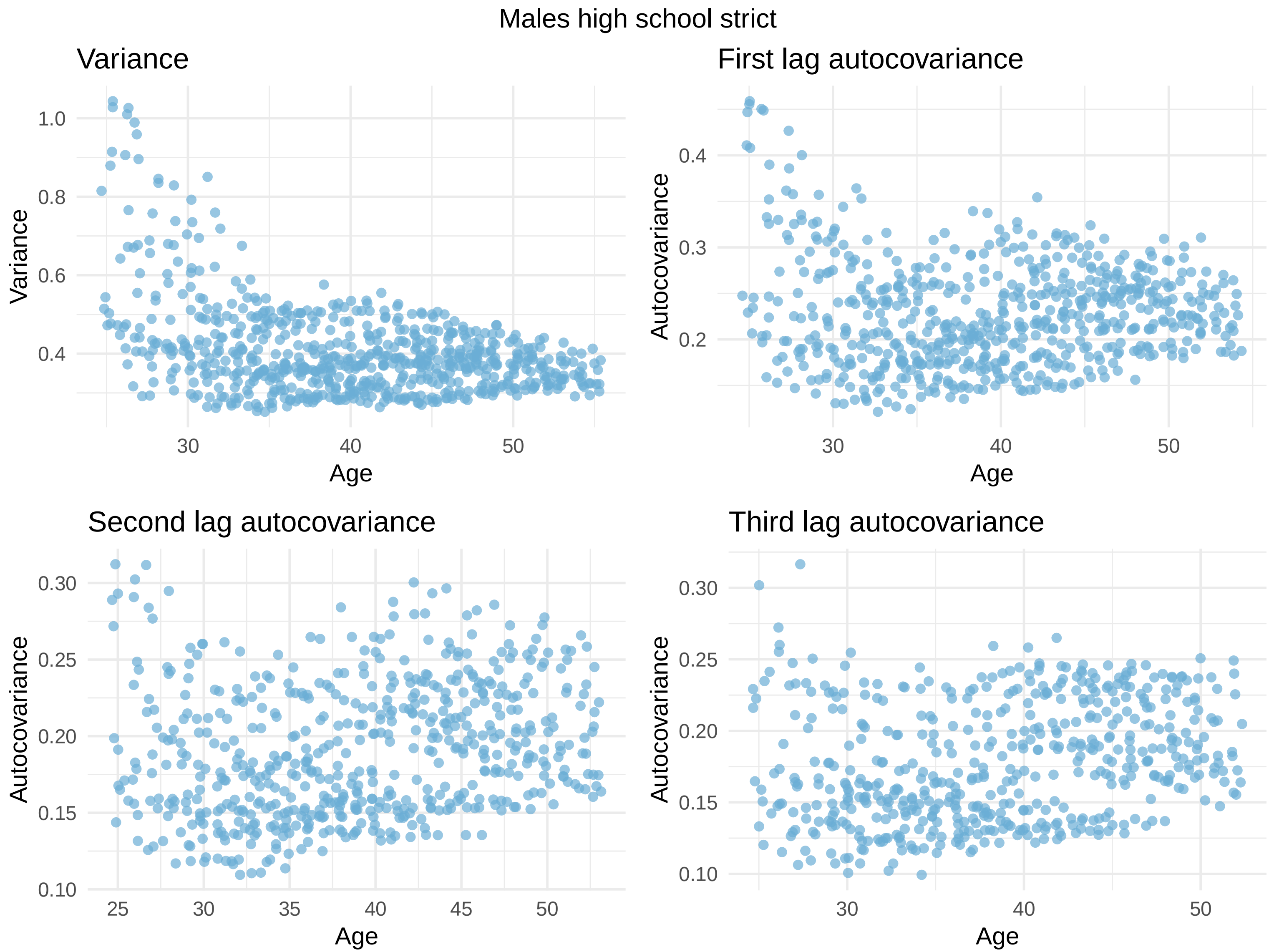

Figure 9: Variance and first three autocovariances of log earnings for males high school strict.

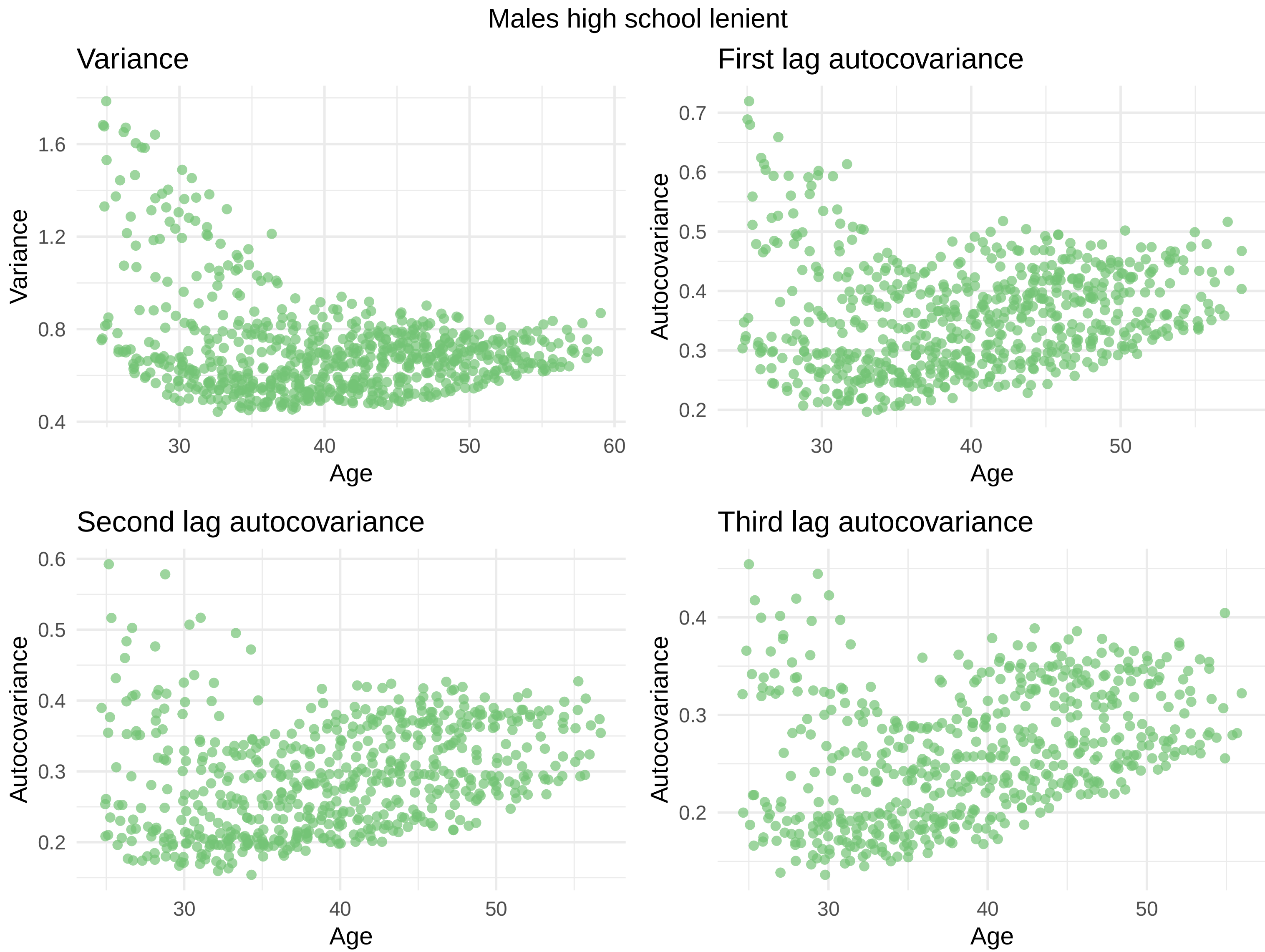

Figure 10: Variance and first three autocovariances of log earnings for males high school lenient.

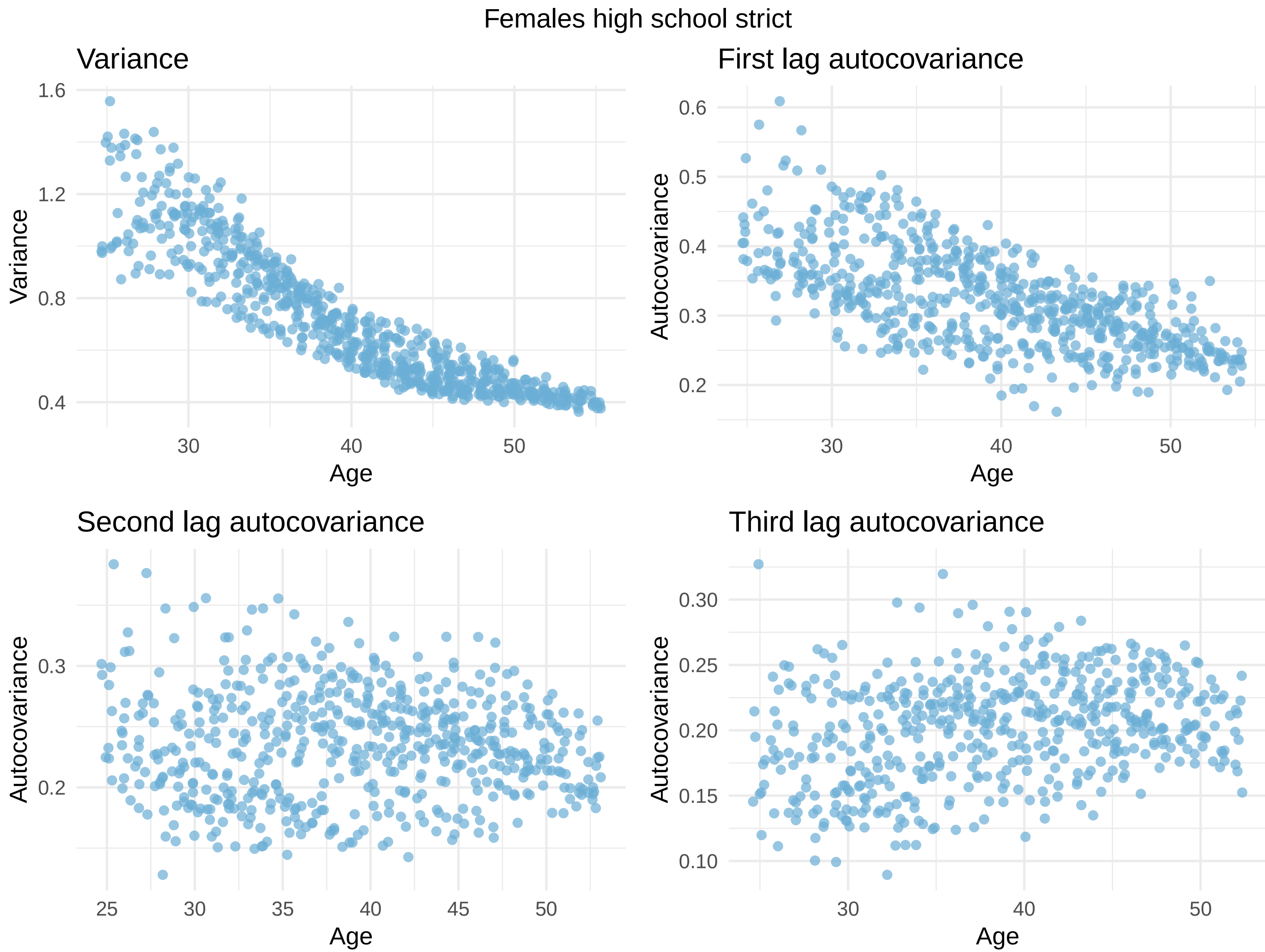

Figure 11: Variance and first three autocovariances of log earnings for females high school strict.

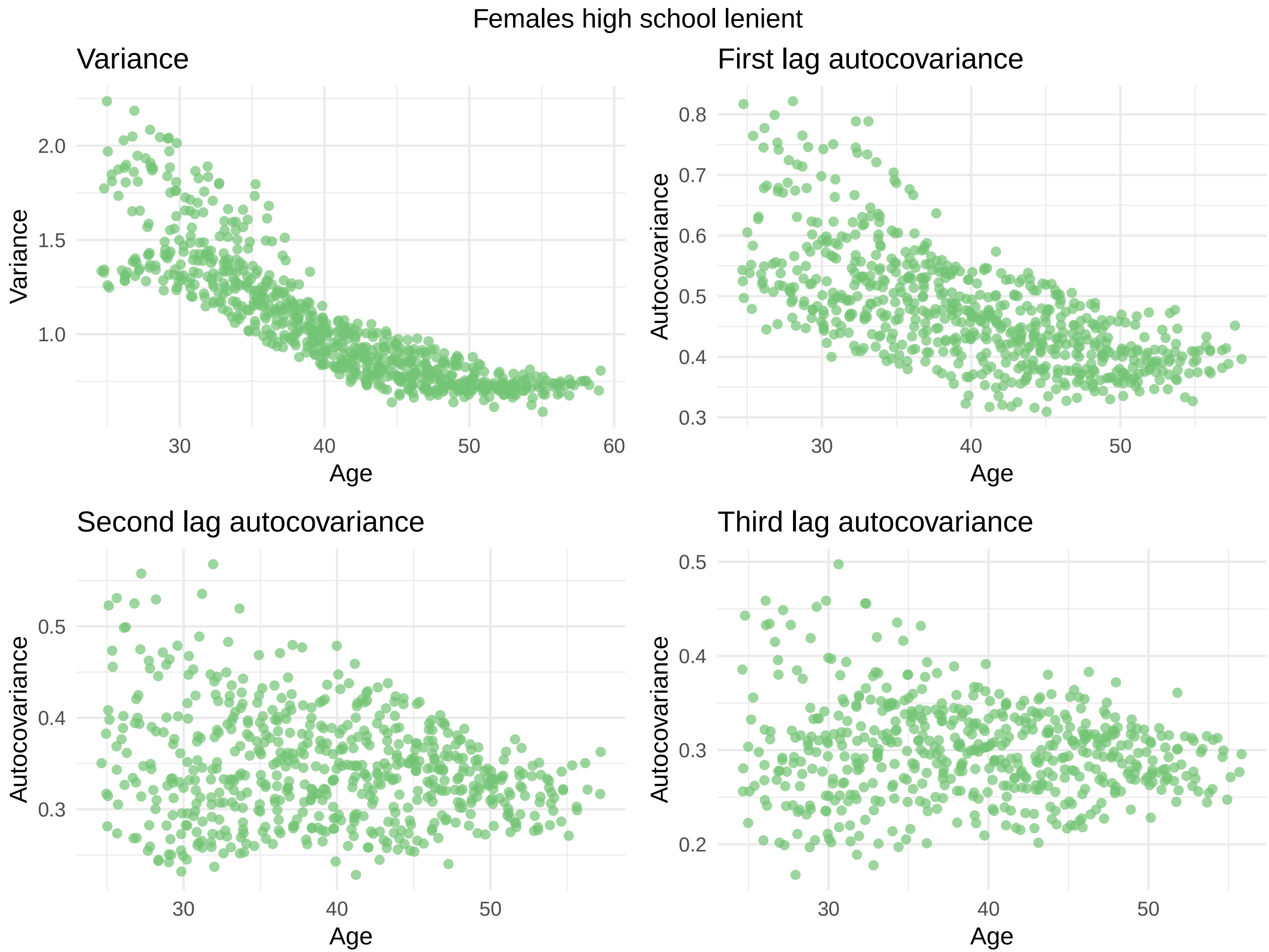

Figure 12: Variance and first three autocovariances of log earnings for females high school lenient.

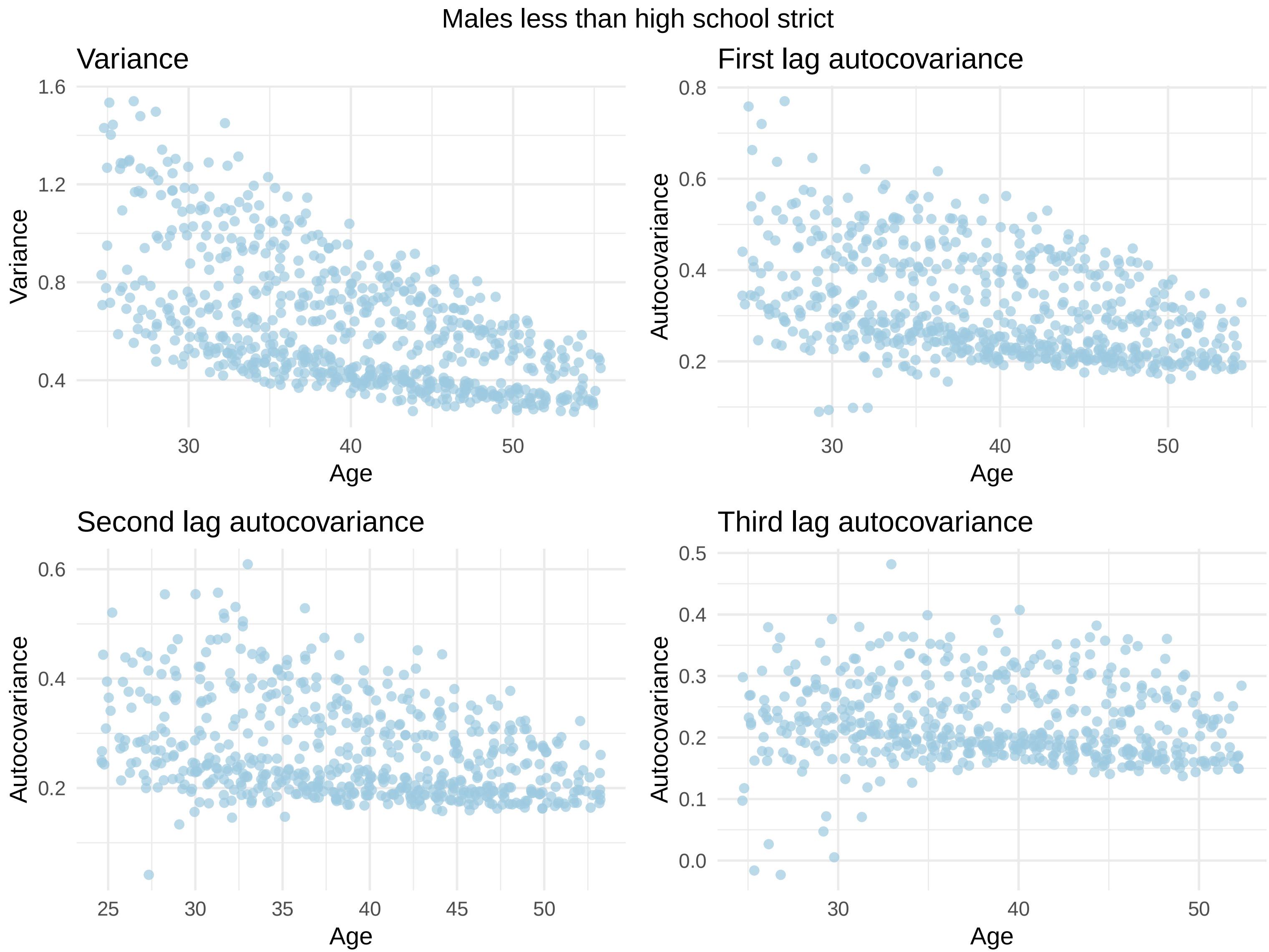

Figure 13: Variance and first three autocovariances of log earnings for males less than high school strict.

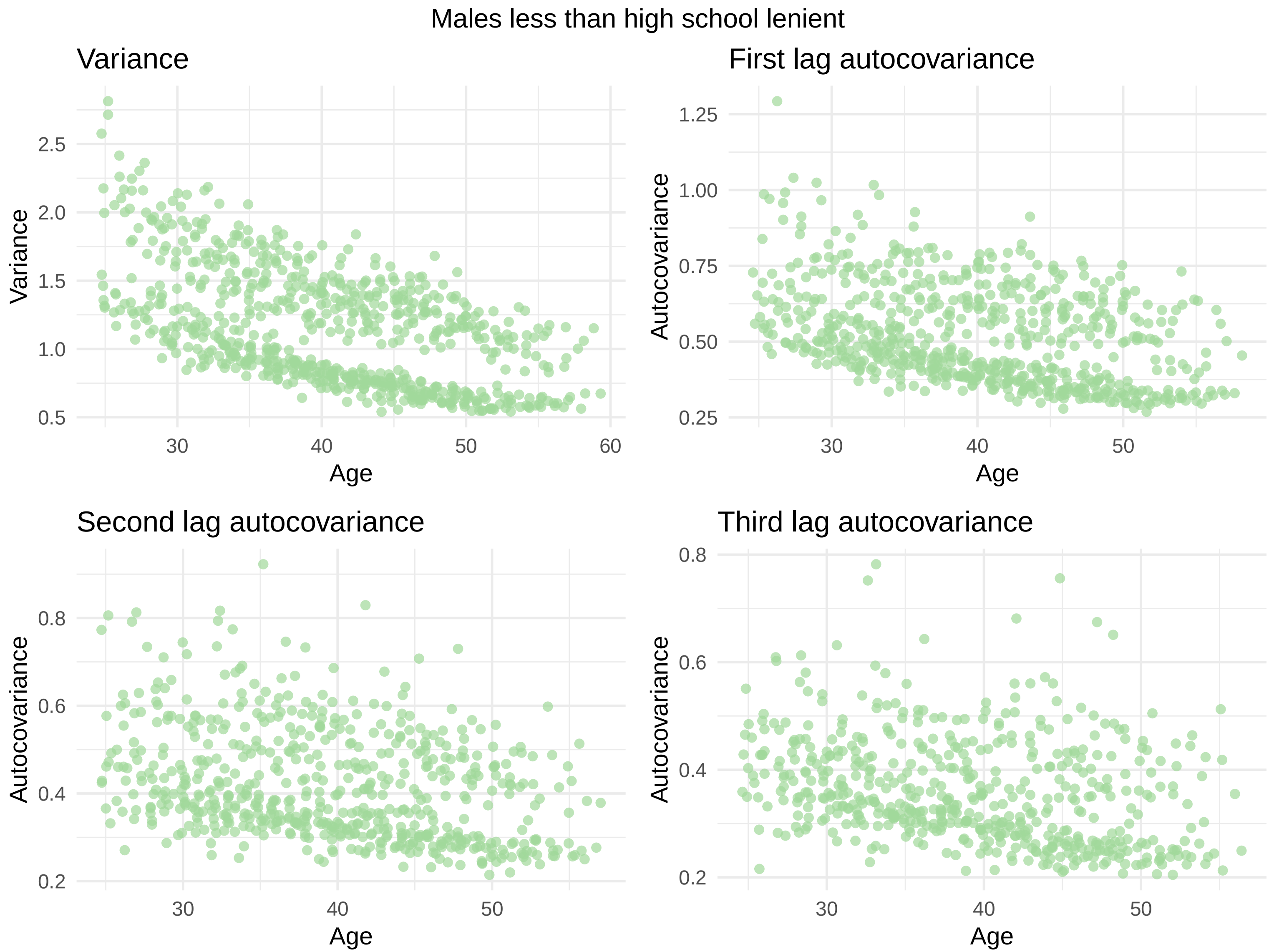

Figure 14: Variance and first three autocovariances of log earnings for males less than high school lenient.

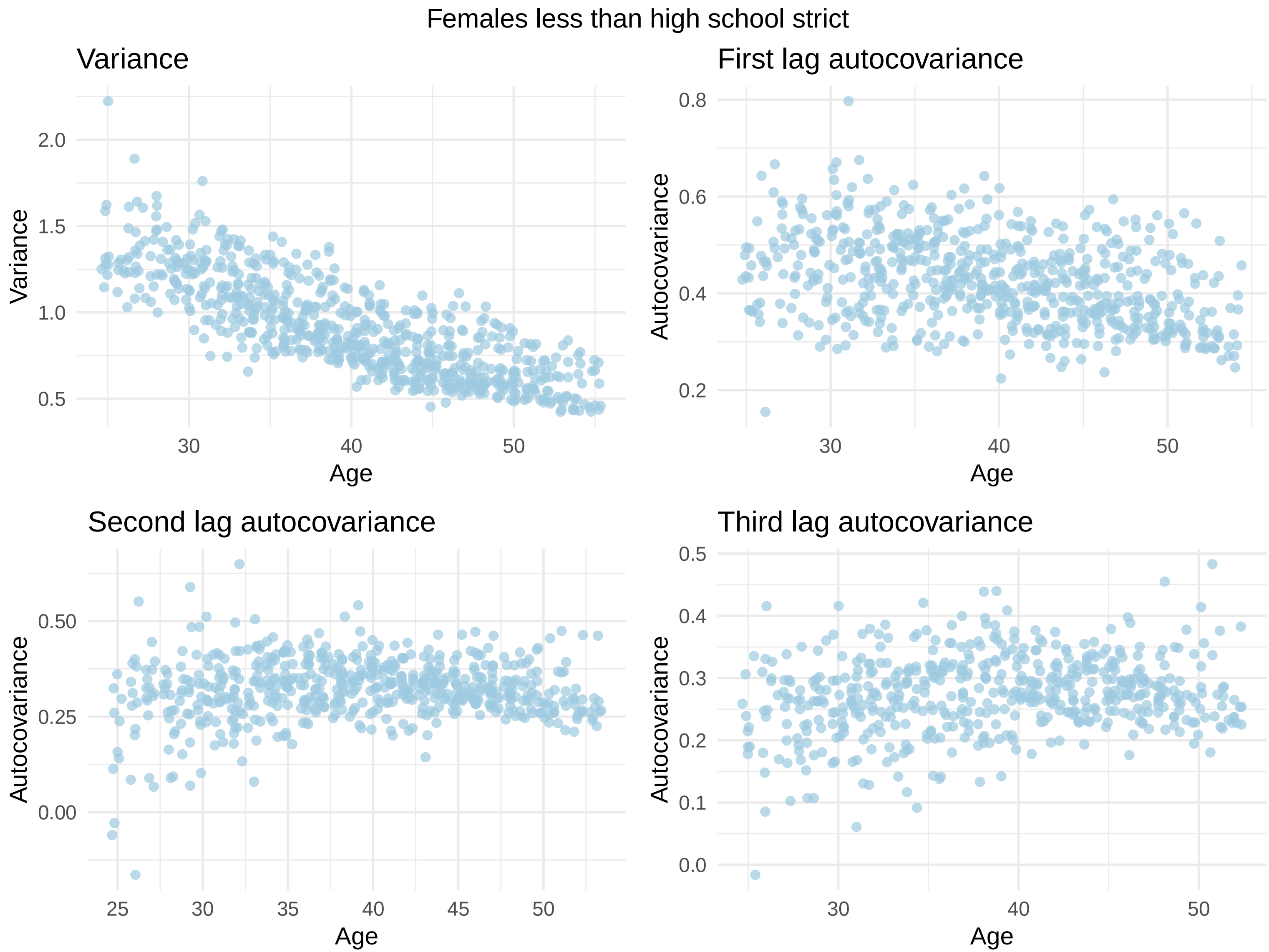

Figure 15: Variance and first three autocovariances of log earnings for females less than high school strict.

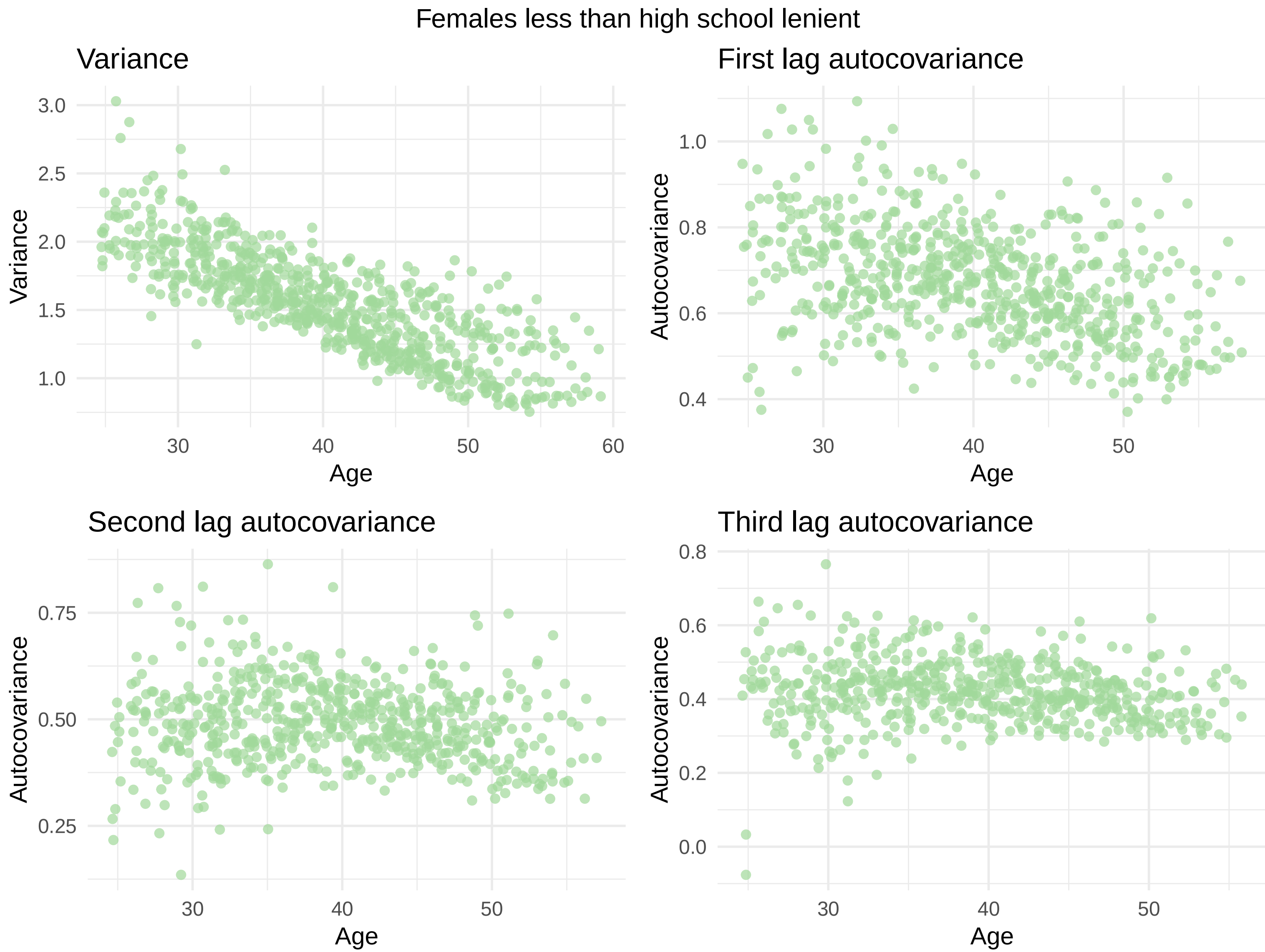

Figure 16: Variance and first three autocovariances of log earnings for females less than high school lenient.

Appendix B: Functional properties of HIP, RIP and hybrid specifications

Consider the very basic random growth specification of residual earnings where experience is proxied by time.

$$\hat{y}_t = \alpha_i + \beta_i t + \epsilon_t \tag{1}$$

$$V_0 = \sigma_\alpha^2 + 2\sigma_{\alpha\beta} t + \sigma_\beta^2 t^2 + \sigma_\epsilon^2 \tag{2}$$

Which corresponds to a second degree polynomial in experience. To determine its functional properties, we examine the first and second derivative of the variance expression with respect to a change in time.

$$\frac{\partial V_0}{\partial t} = 2\sigma_{\alpha\beta} + 2\sigma_\beta^2 t \tag{3}$$

The first derivative is allowed to be negative initially due to the ambiguity concerning the covariance, but will eventually turn positive.

$$\frac{\partial^2 V_0}{\partial t^2} = 2\sigma_\beta^2 \tag{4}$$

Since σ_β^2 is limited to positive values, V_0 has to be convex in time for it to be compatible with the random growth specification.

Now let's introduce a random walk component to the random growth specification in equation (15).

$$\hat{y}_t = \hat{y}_{t-1} + \alpha_i + \beta_i t + \epsilon_t \tag{5}$$

$$V_0 = \sigma_\alpha^2 + 2\sigma_{\alpha\beta} t + \sigma_\beta^2 t^2 + t\sigma_\epsilon^2 \tag{6}$$

The variance of this specification evolves linearly by both the covariance term and by the variance of the innovation. This invokes an identification problem as it is not obvious how these components could be separated and subsequently identified from the autocovariance matrix.

$$\frac{\partial V_0}{\partial t} = 2\sigma_{\alpha\beta} + 2\sigma_\beta^2 t + \sigma_\epsilon^2 \tag{7}$$

$$\frac{\partial^2 V_0}{\partial t^2} = 2\sigma_\beta^2 \tag{8}$$

This model would also fall short for explaining any variance evolution other than a convex function due to the statistical limit of variances being positive.

Appendix C: Bias induced by white Gaussian noise on the serially correlated innovation process

Consider the following MA(1) process, z_t.

$$z_t = \eta_t + \phi\eta_{t-1} \tag{9}$$

$$\eta \sim iid(0, \sigma_\eta^2) \tag{10}$$

In first differences, the innovation of such process will only affect the first and second order autocovariance moments.

$$\gamma_0 = E[\Delta z_t^2] = \sigma_\eta^2(1 + \phi^2) \tag{11}$$

$$\gamma_1 = E[(\Delta z_t)(\Delta z_{t-1})] = \phi\sigma_\eta^2 \tag{12}$$

Next we compare the evolution of such a process with another moving average process, x_t, altered to contain an additional white noise term.

$$x_t = \epsilon_t + \theta\epsilon_{t-1} + e_t \tag{13}$$

$$\epsilon \sim iid(0, \sigma_\epsilon^2) \tag{14}$$

$$e \sim iid(0, \sigma_e^2) \tag{15}$$

With corresponding first and second order autocovariance moments:

$$\psi_0 = E[\Delta x_t^2] = \sigma_\epsilon^2(1 + \theta^2) + \sigma_e^2 \tag{16}$$

$$\psi_1 = E[(\Delta x_t)(\Delta x_{t-1})] = \theta\sigma_\epsilon^2 \tag{17}$$

Finally we compare the ratios of moments of both processes.

$$\frac{\gamma_1}{\gamma_0} = \frac{\phi}{(1 + \phi^2)} \tag{18}$$

$$\frac{\psi_1}{\psi_0} = \frac{\theta}{(1 + \theta^2 + (\sigma_e^2/\sigma_\epsilon^2))} \tag{19}$$

$$\frac{\theta}{(1 + \theta^2 + (\sigma_e^2/\sigma_\epsilon^2))} \geq \frac{\phi}{(1 + \phi^2)} \tag{20}$$

$$\lim_{\sigma_e^2 \to 0} \phi = \theta \tag{21}$$

Only if σ_e^2 goes to zero, ϕ will provide an unbiased estimator of θ. This should be of concern mainly for survey data, as the objective nature of register data should minimize its occurrence.

Appendix: Earnings dynamics in Sweden

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May 2019

Appendix

Appendix A: Empirical variance and fist three covariances by gender and filter

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†Umeå University, e-mail: johan.holmberg@umu.se

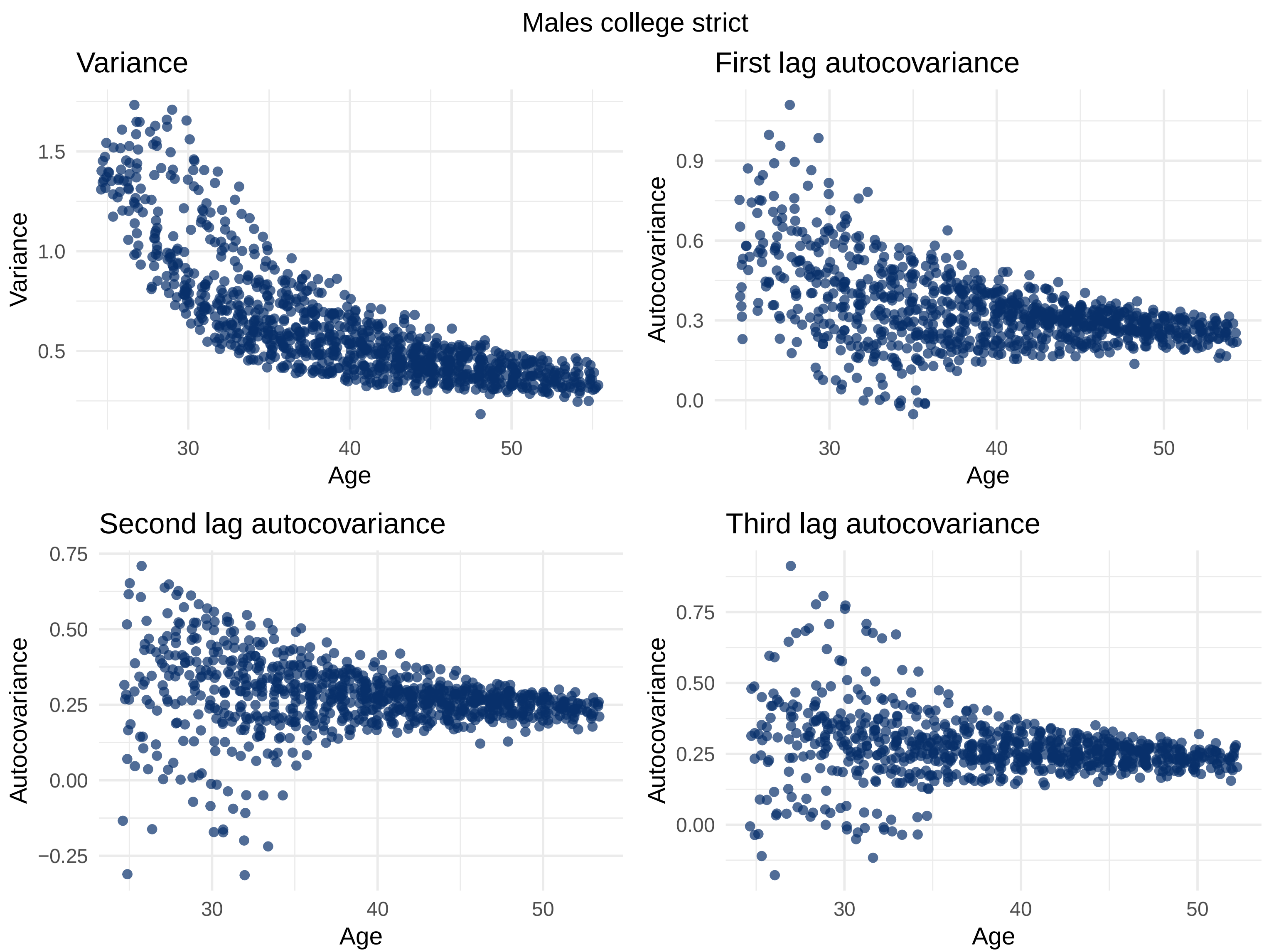

Figure 1: Variance and first three autocovariances of log earnings for males college strict.

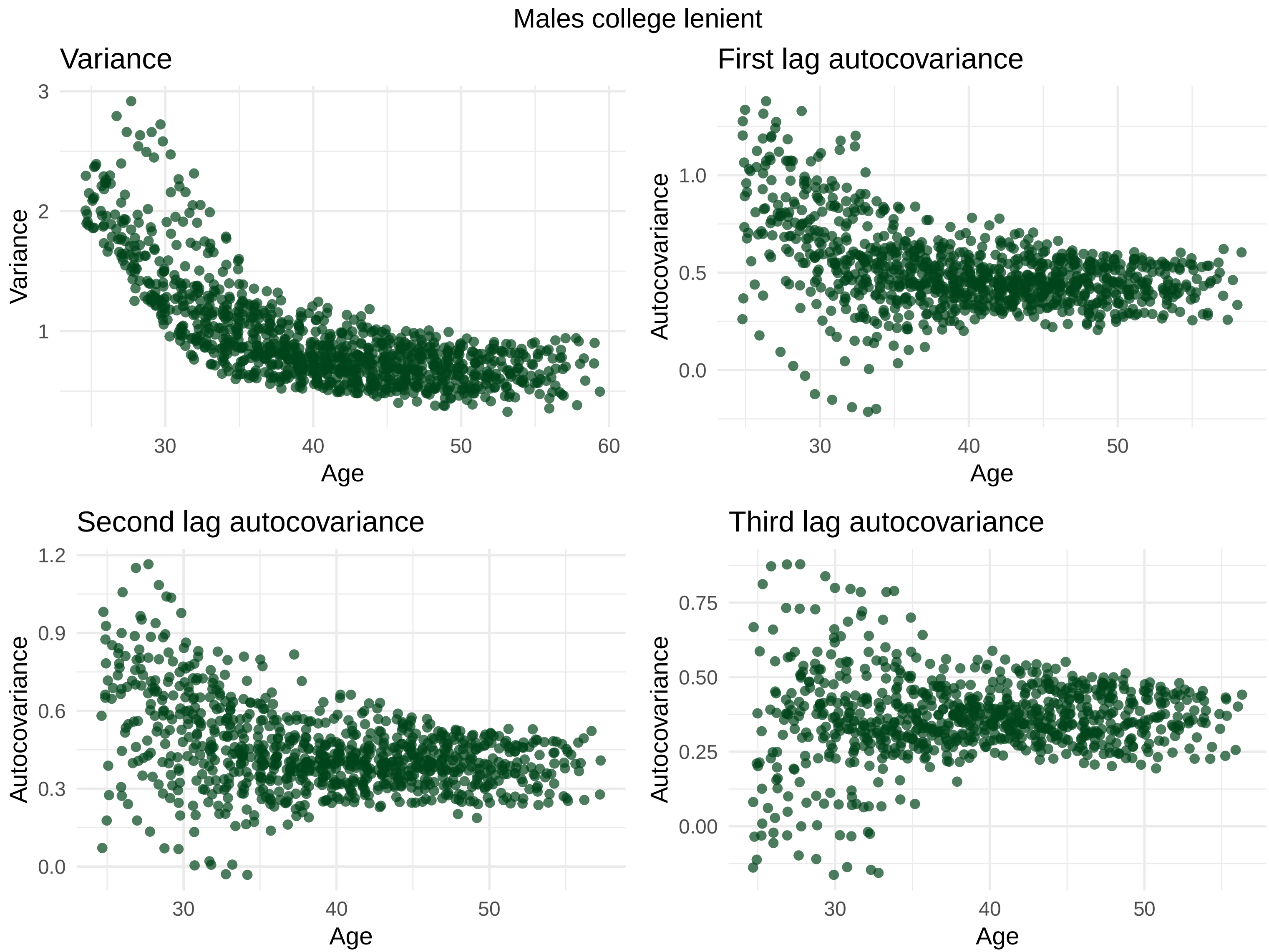

Figure 2: Variance and first three autocovariances of log earnings for males college lenient

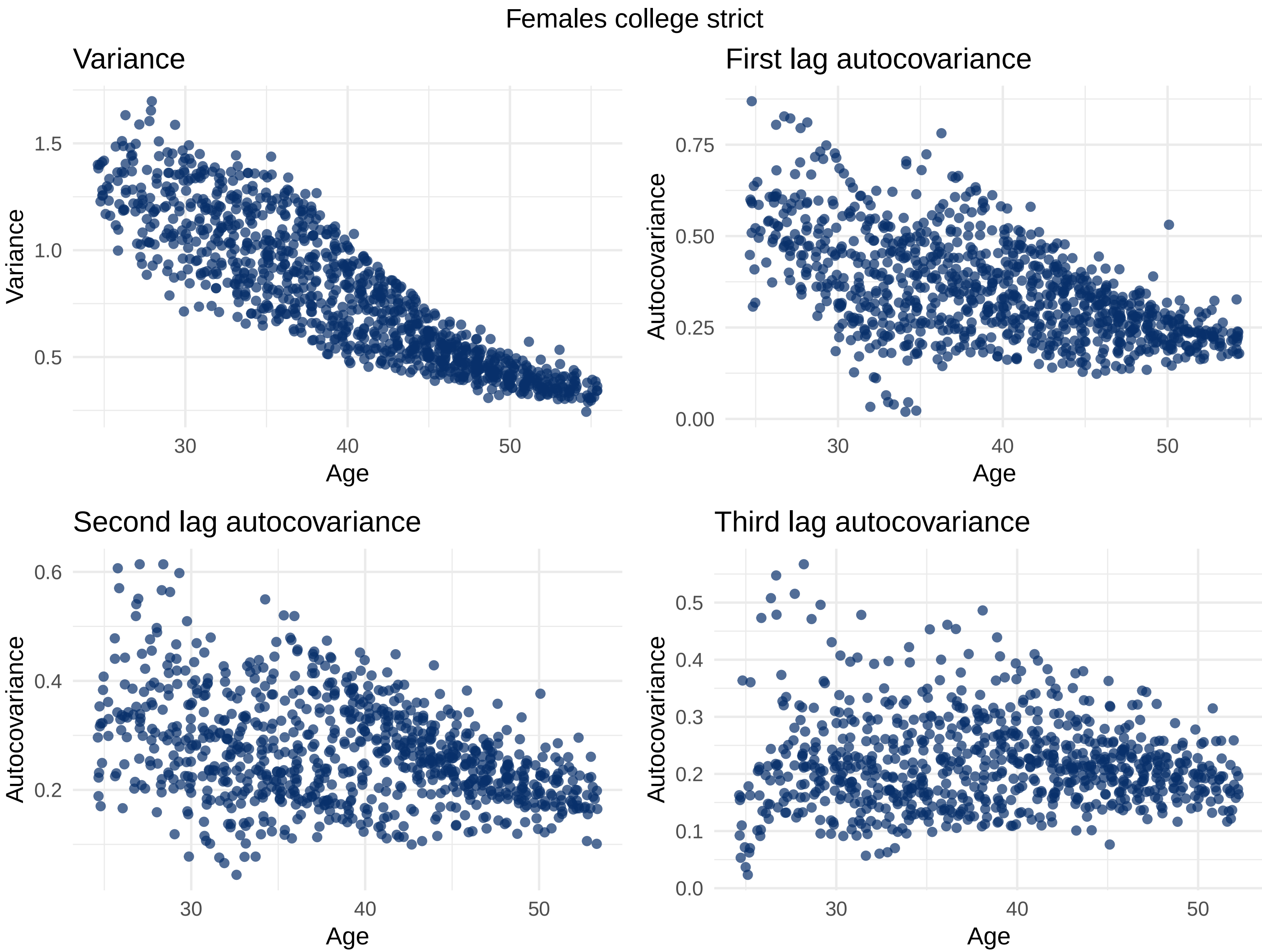

Figure 3: Variance and first three autocovariances of log earnings for females college strict.

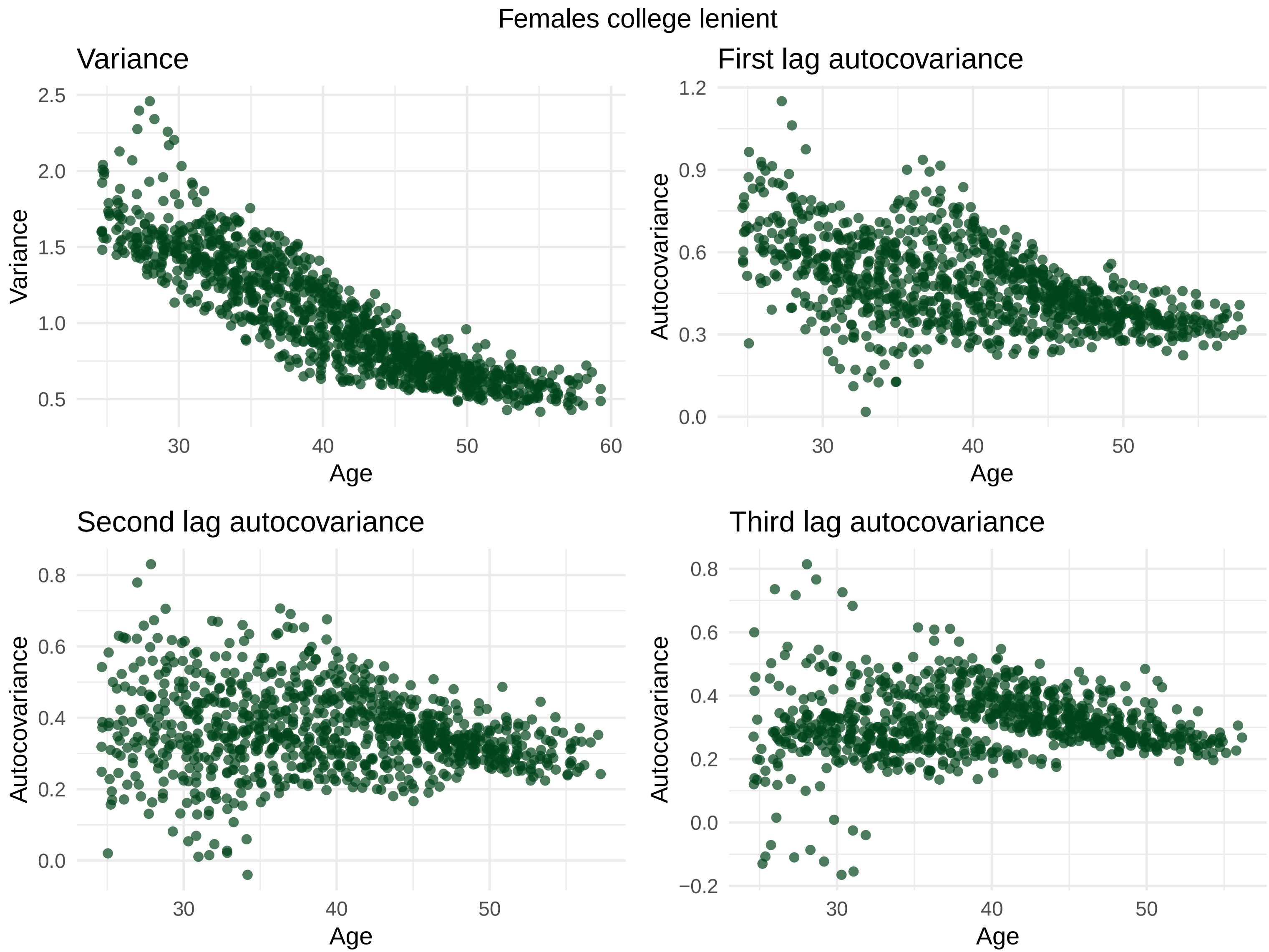

Figure 4: Variance and first three autocovariances of log earnings for females college lenient.

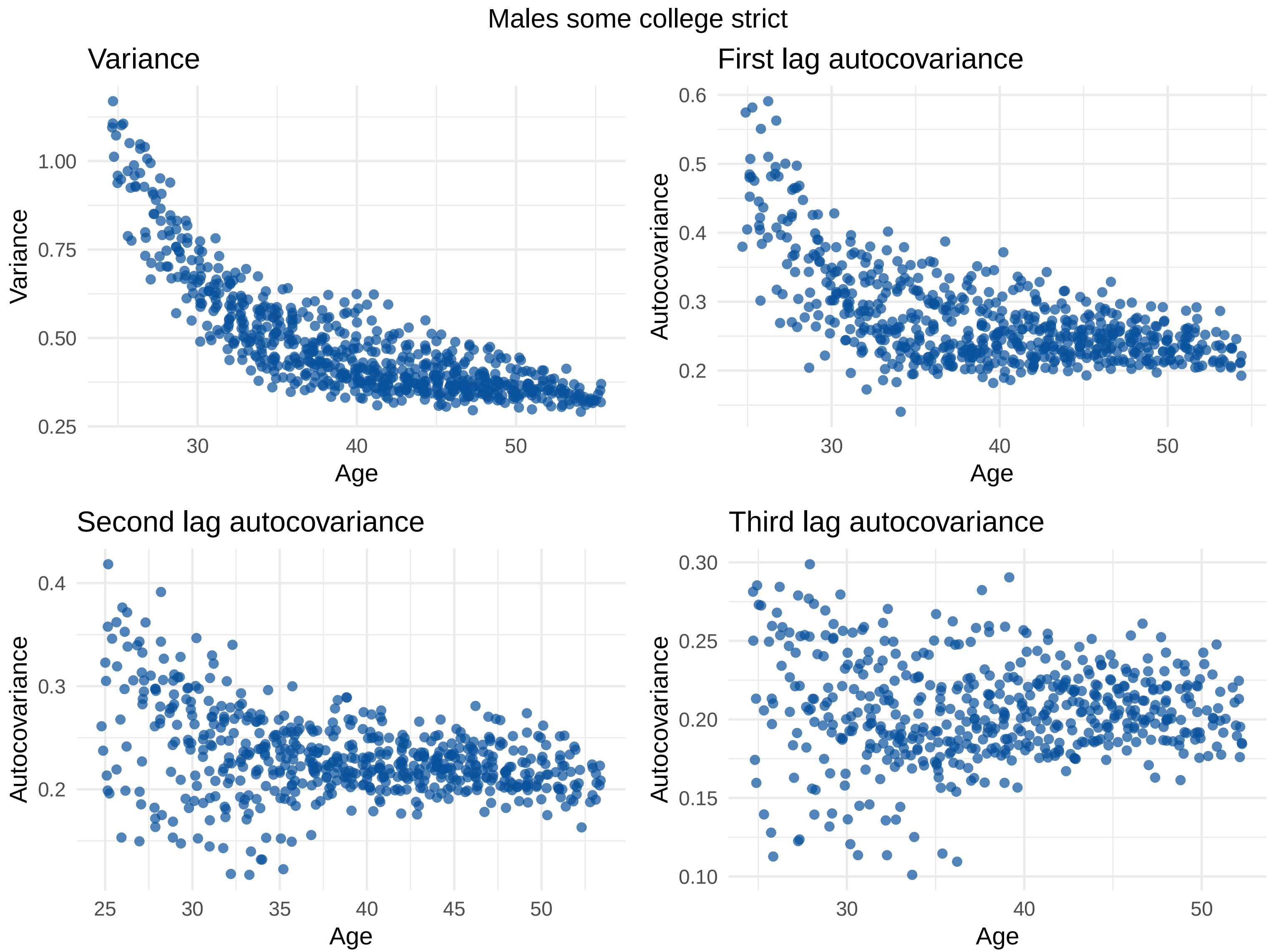

Figure 5: Variance and first three autocovariances of log earnings for males some college strict.

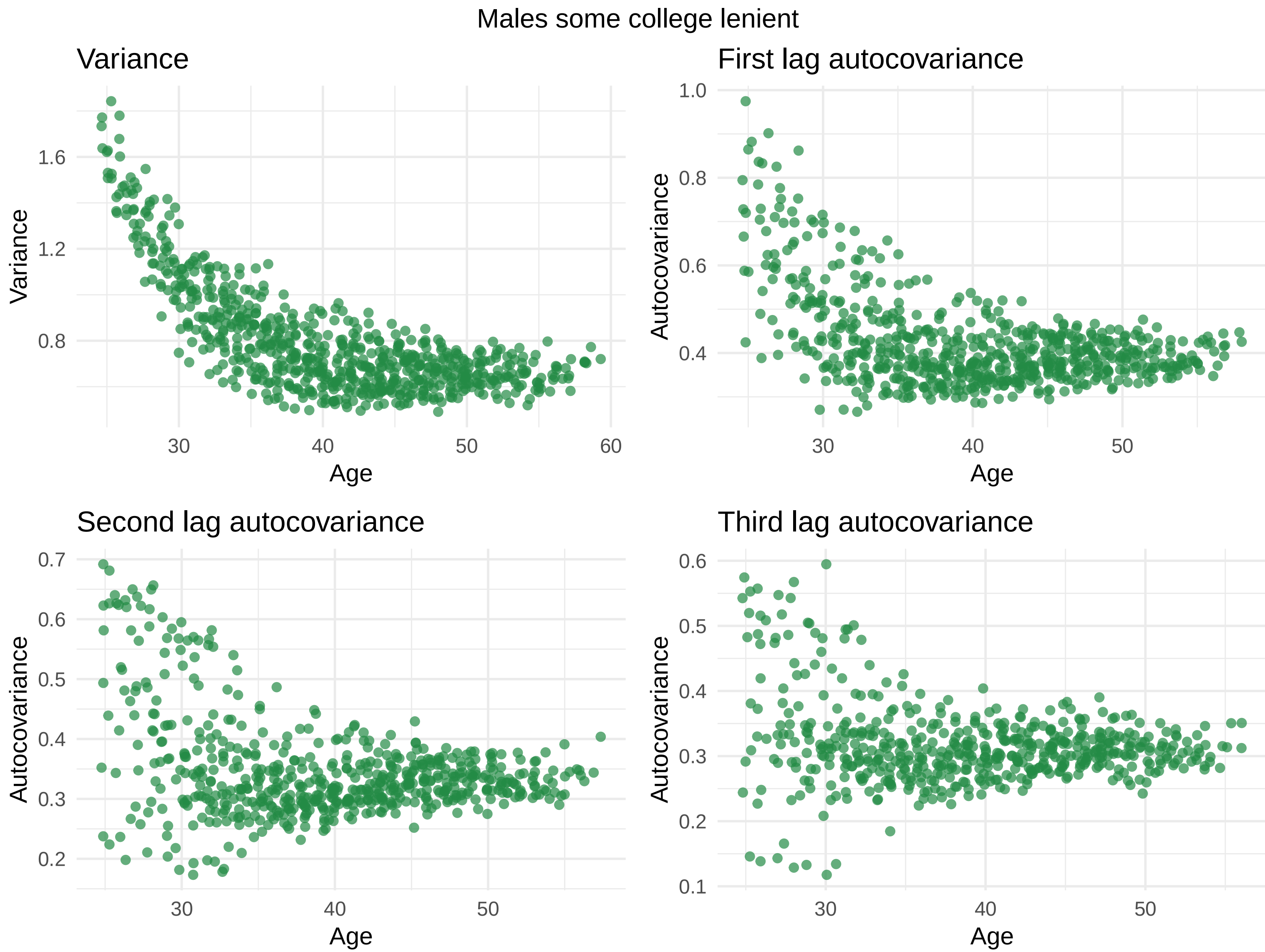

Figure 6: Variance and first three autocovariances of log earnings for males some college lenient.

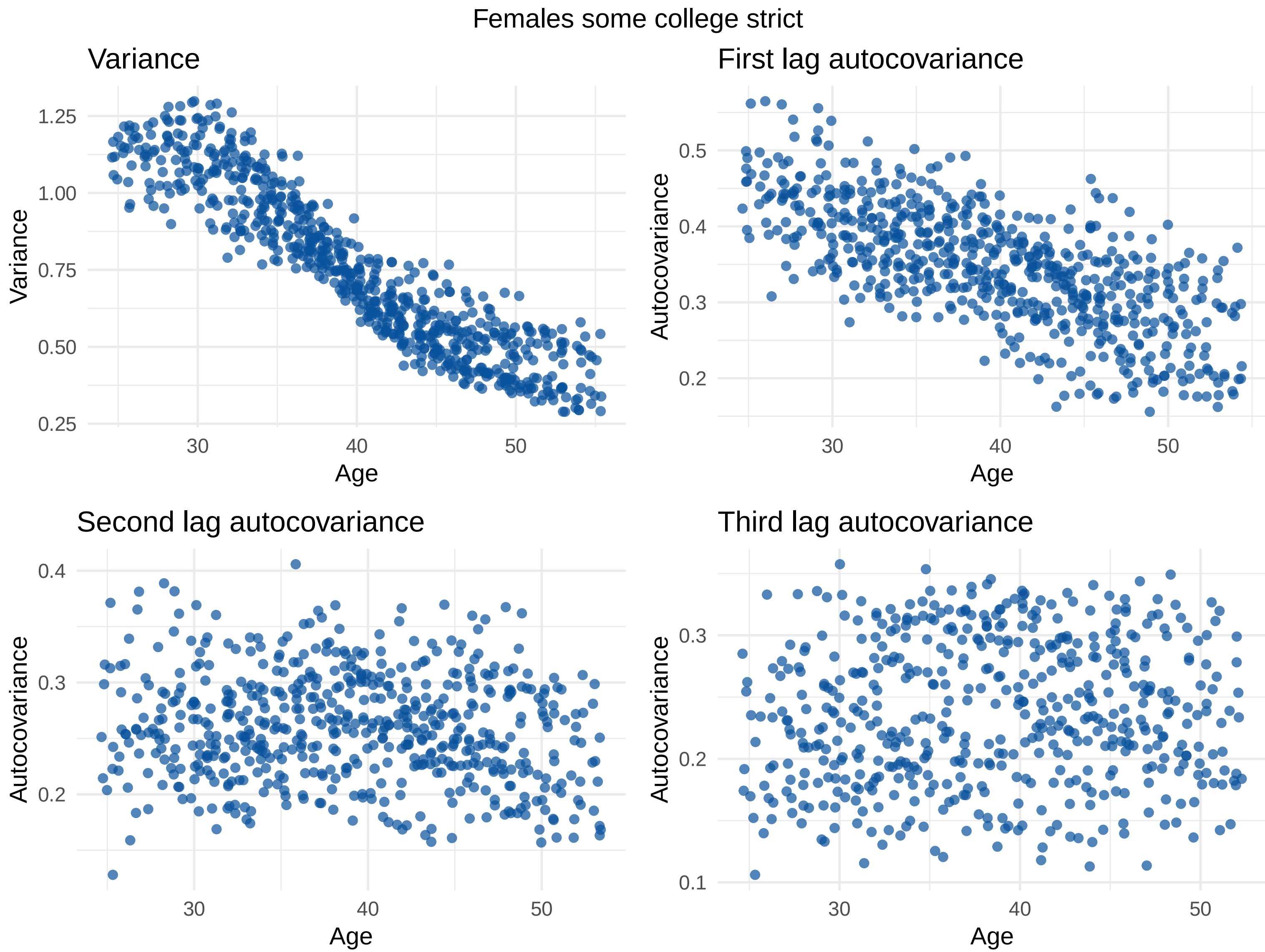

Figure 7: Variance and first three autocovariances of log earnings for females some college strict.

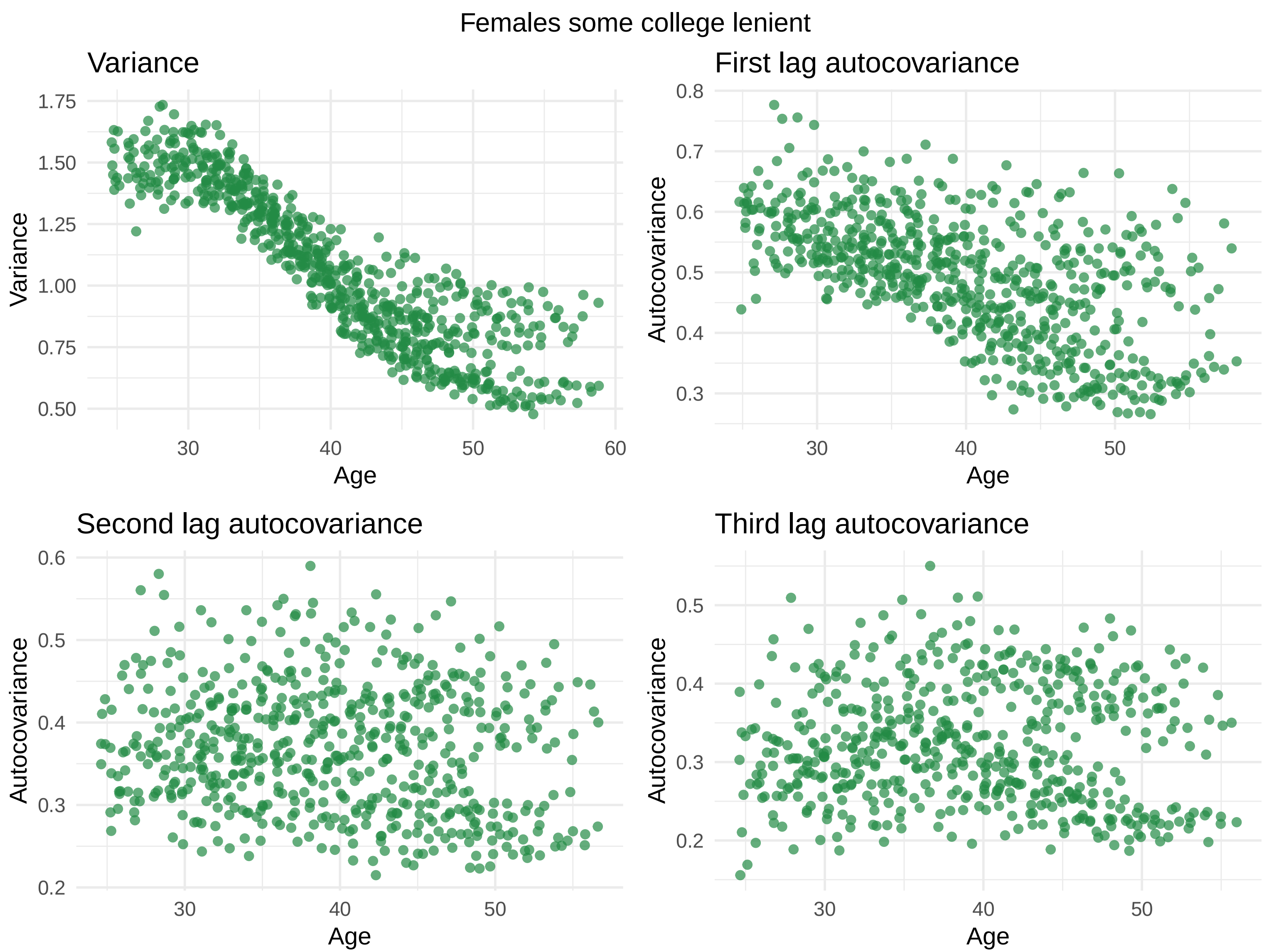

Figure 8: Variance and first three autocovariances of log earnings for females some college lenient.

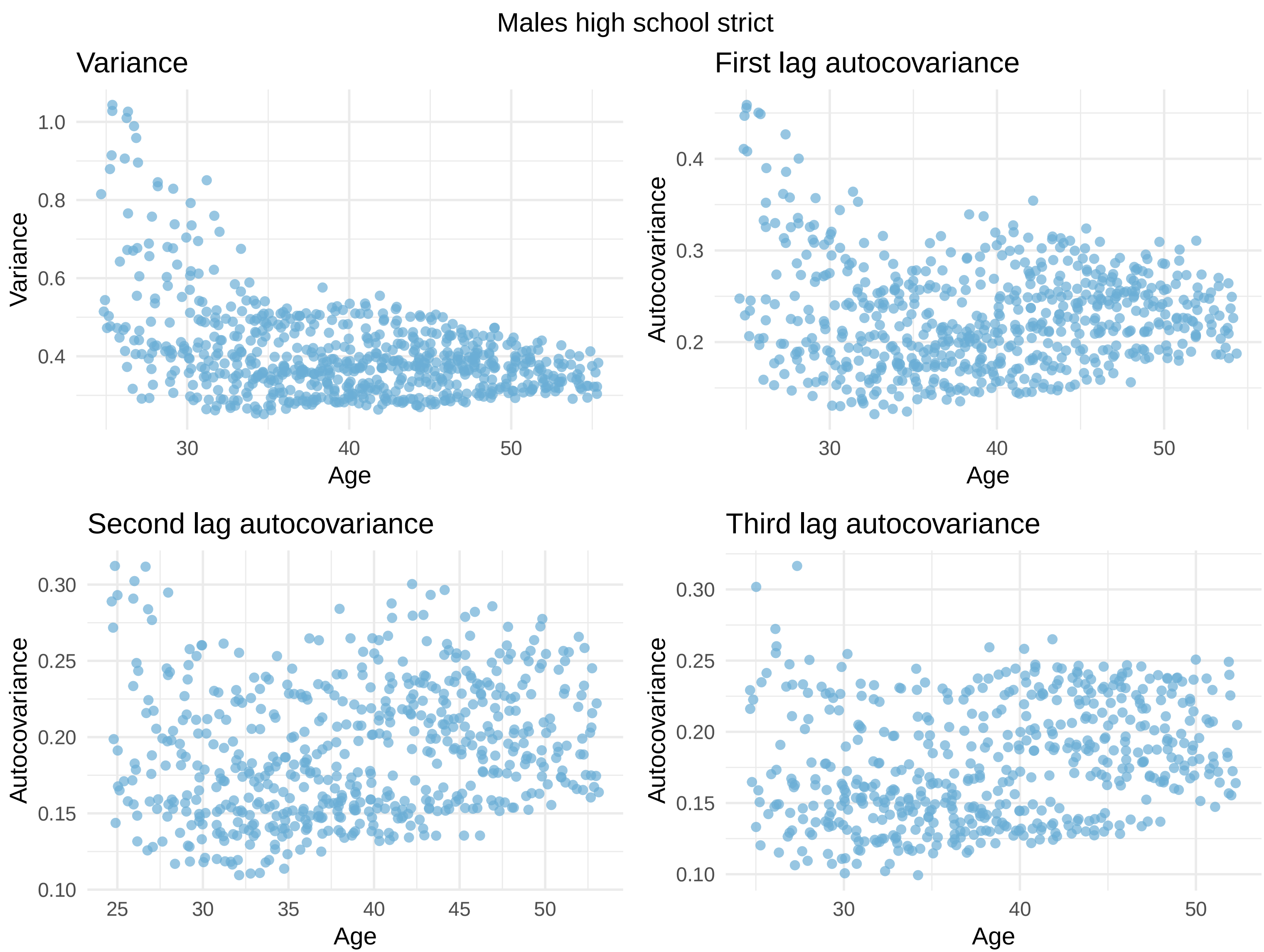

Figure 9: Variance and first three autocovariances of log earnings for males high school strict.

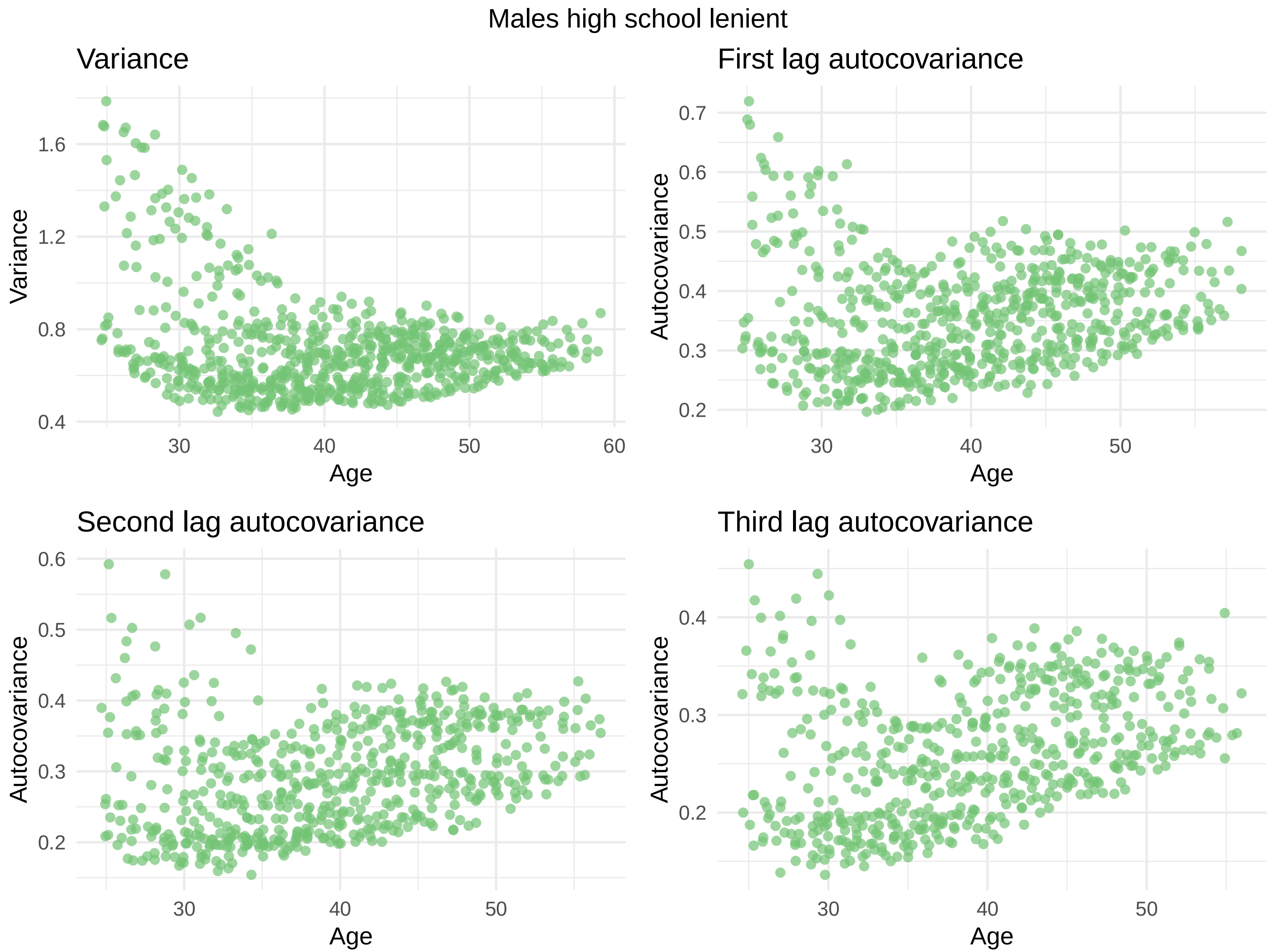

Figure 10: Variance and first three autocovariances of log earnings for males high school lenient.

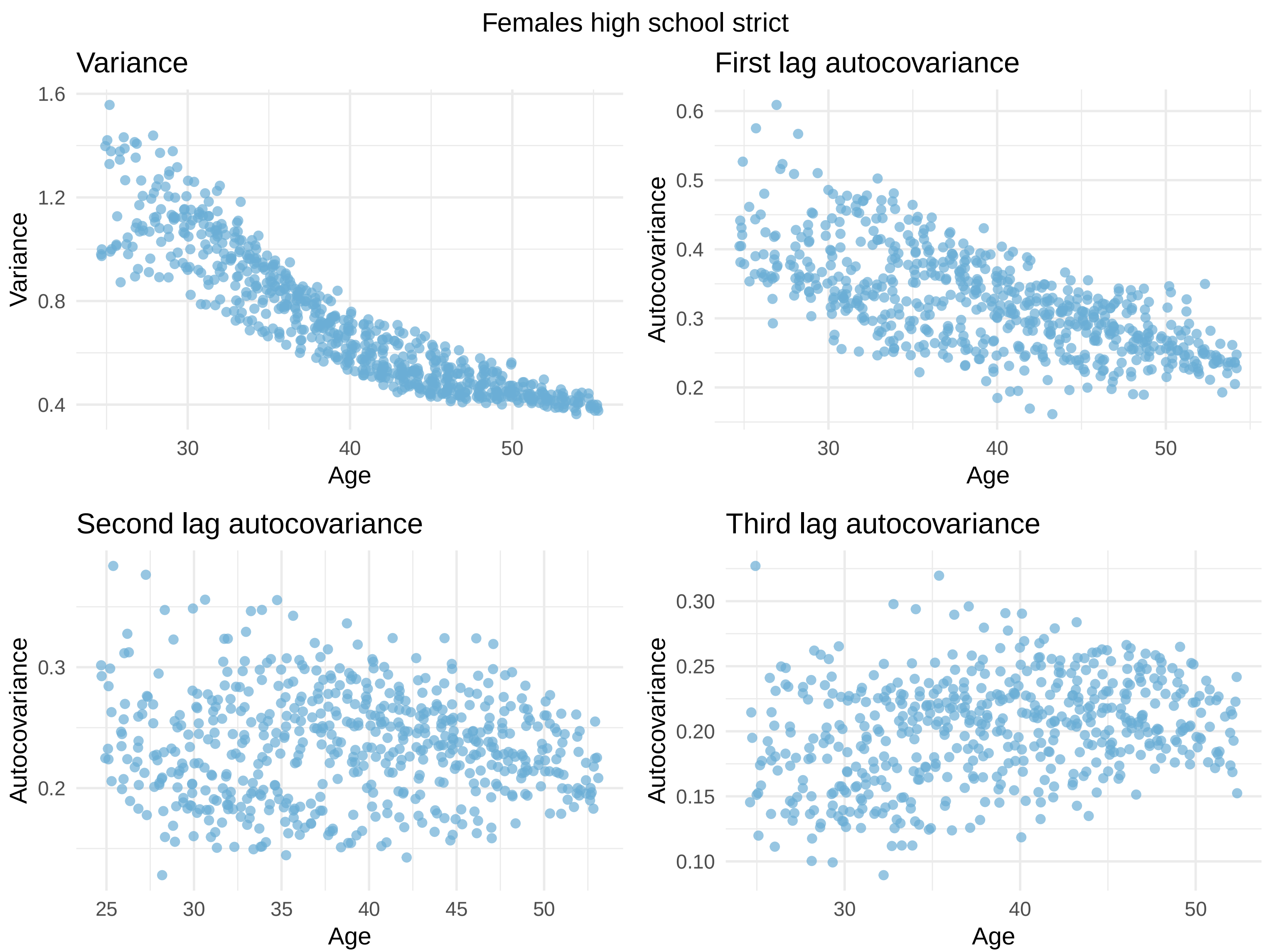

Figure 11: Variance and first three autocovariances of log earnings for females high school strict.

Figure 12: Variance and first three autocovariances of log earnings for females high school lenient.

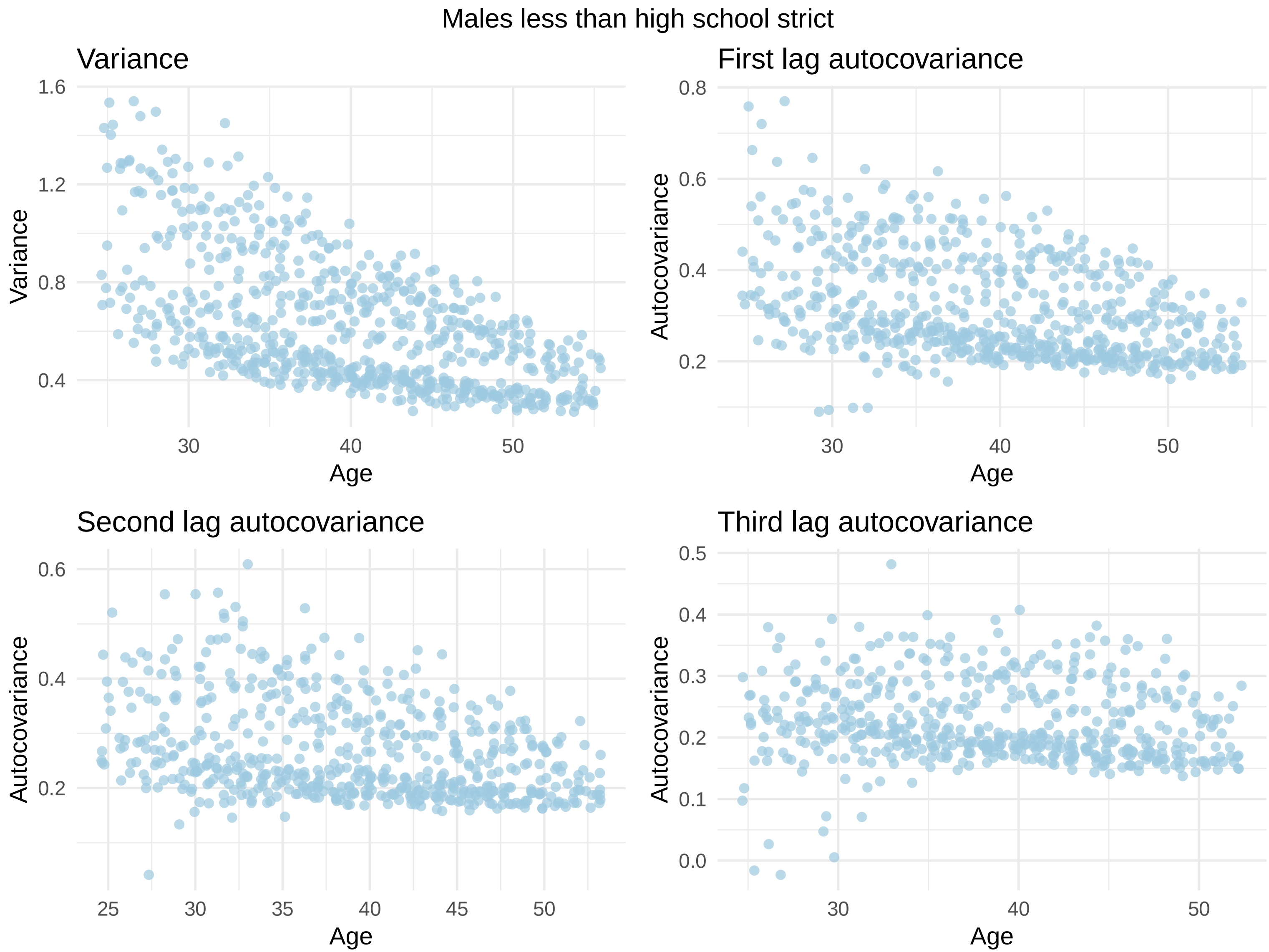

Figure 13: Variance and first three autocovariances of log earnings for males less than high school strict.

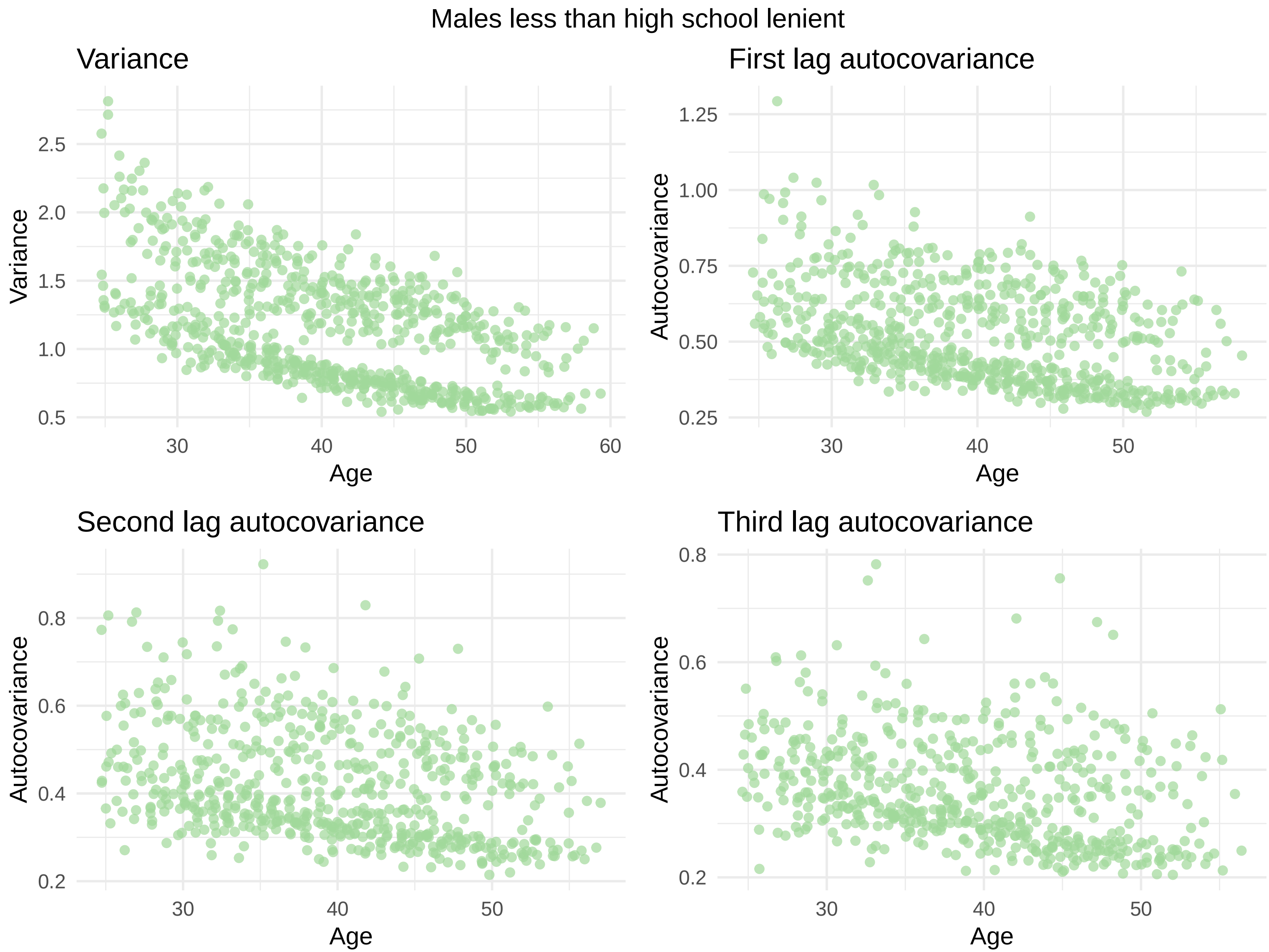

Figure 14: Variance and first three autocovariances of log earnings for males less than high school lenient.

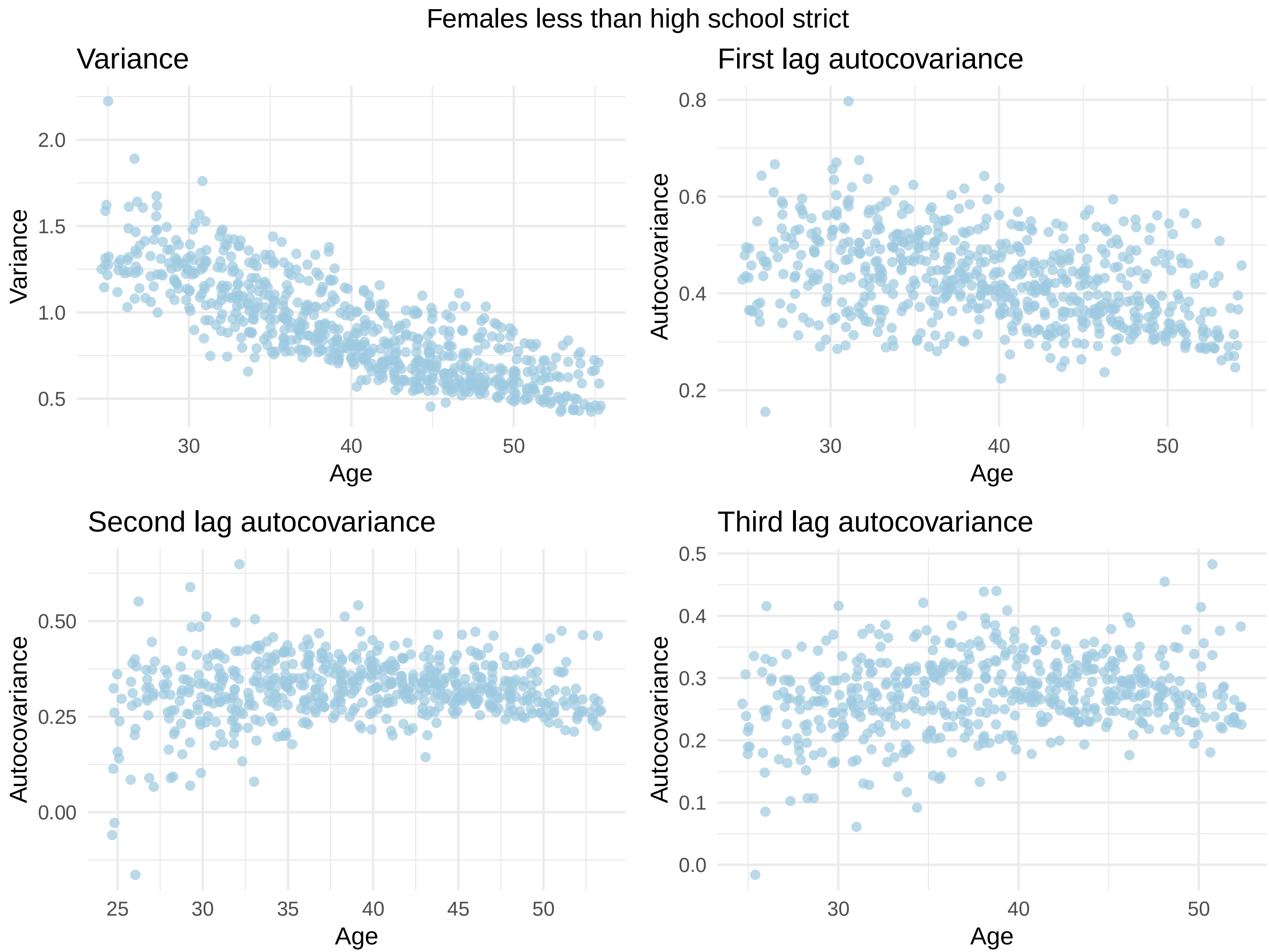

Figure 15: Variance and first three autocovariances of log earnings for females less than high school strict.

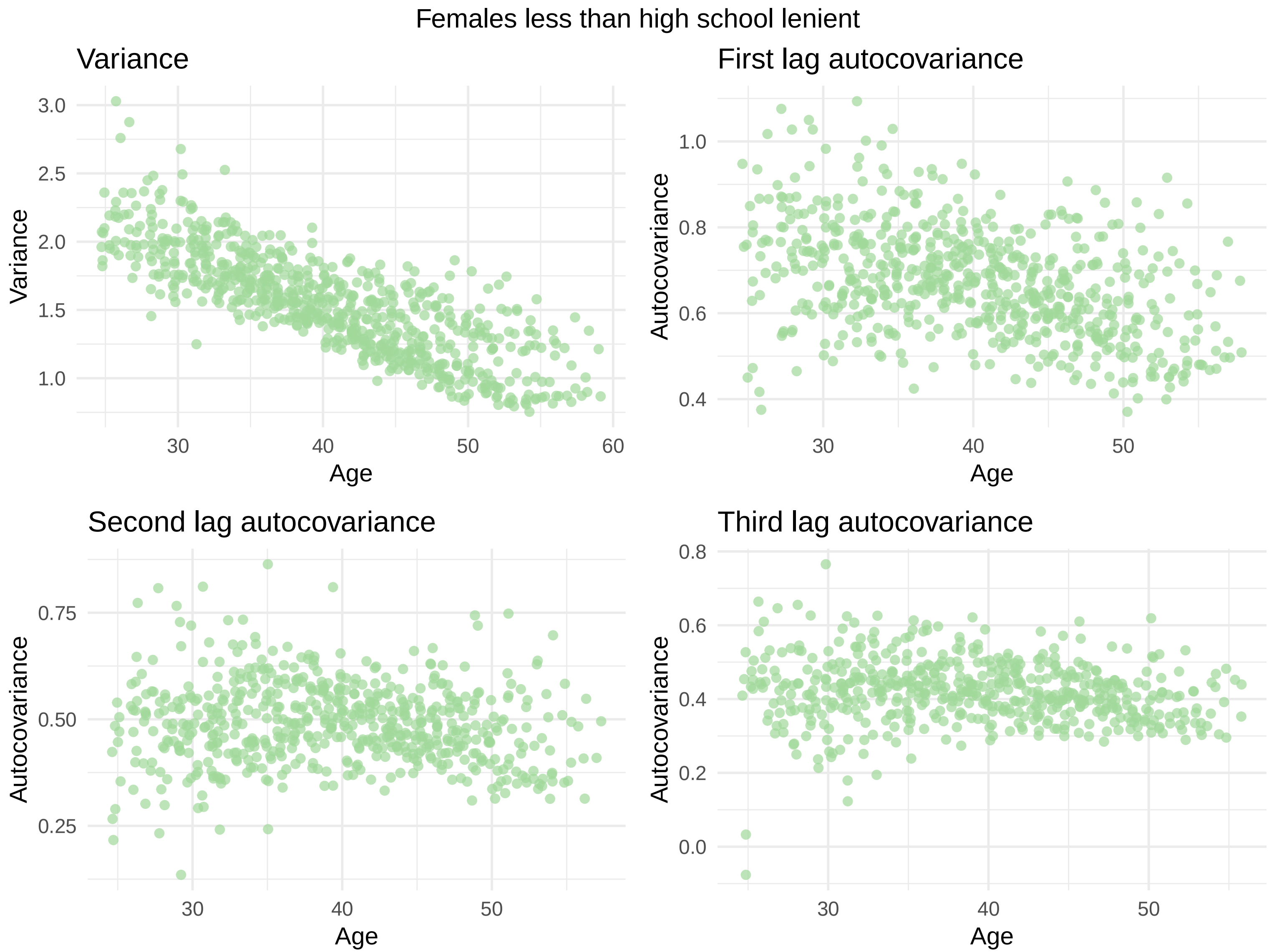

Figure 16: Variance and first three autocovariances of log earnings for females less than high school lenient.

Appendix D: Model fit and residuals

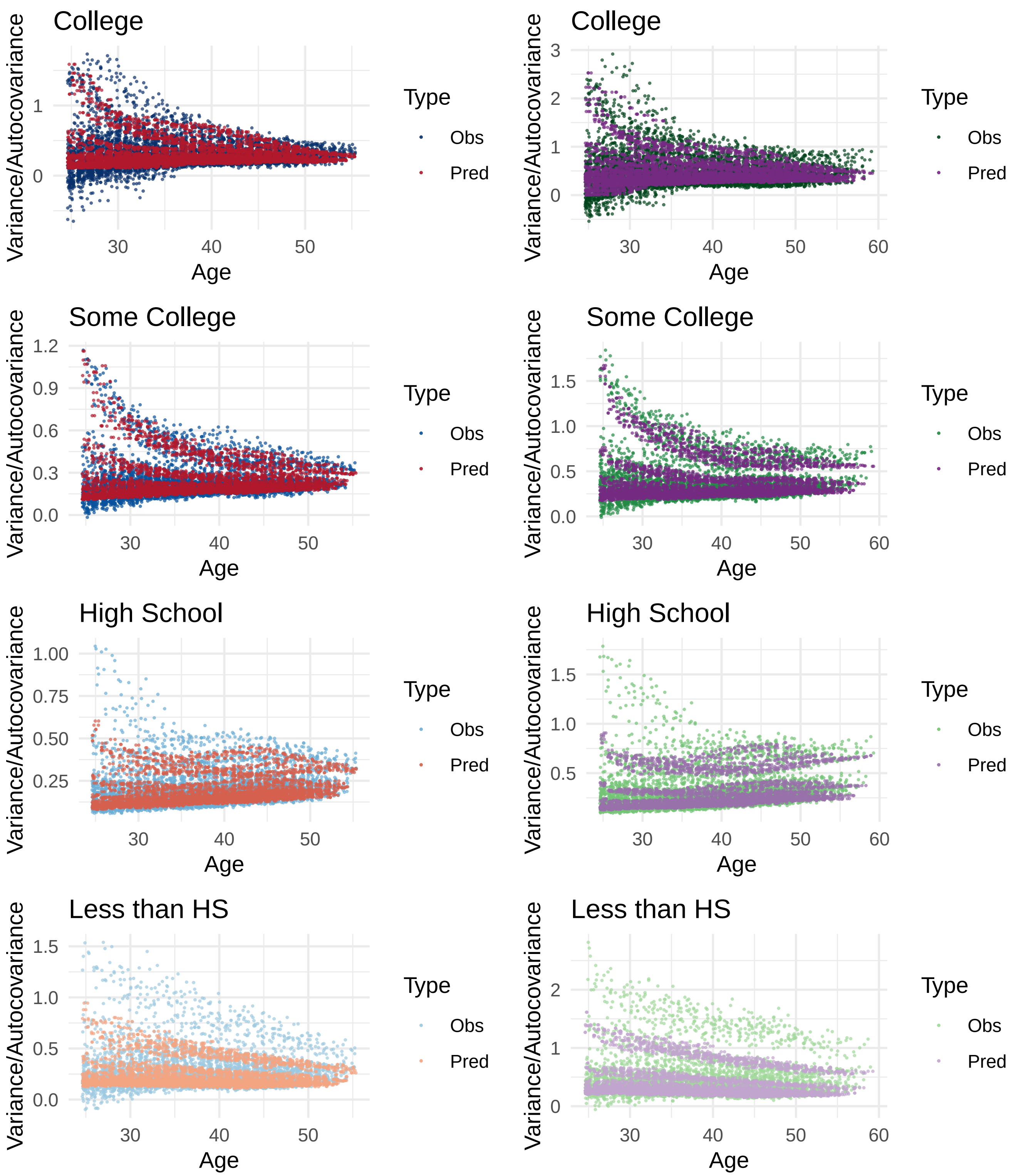

Figure 1: Predicted and observed second order moments males.
Note: Right hand column corresponds to the strict samples and the left to the lenient.

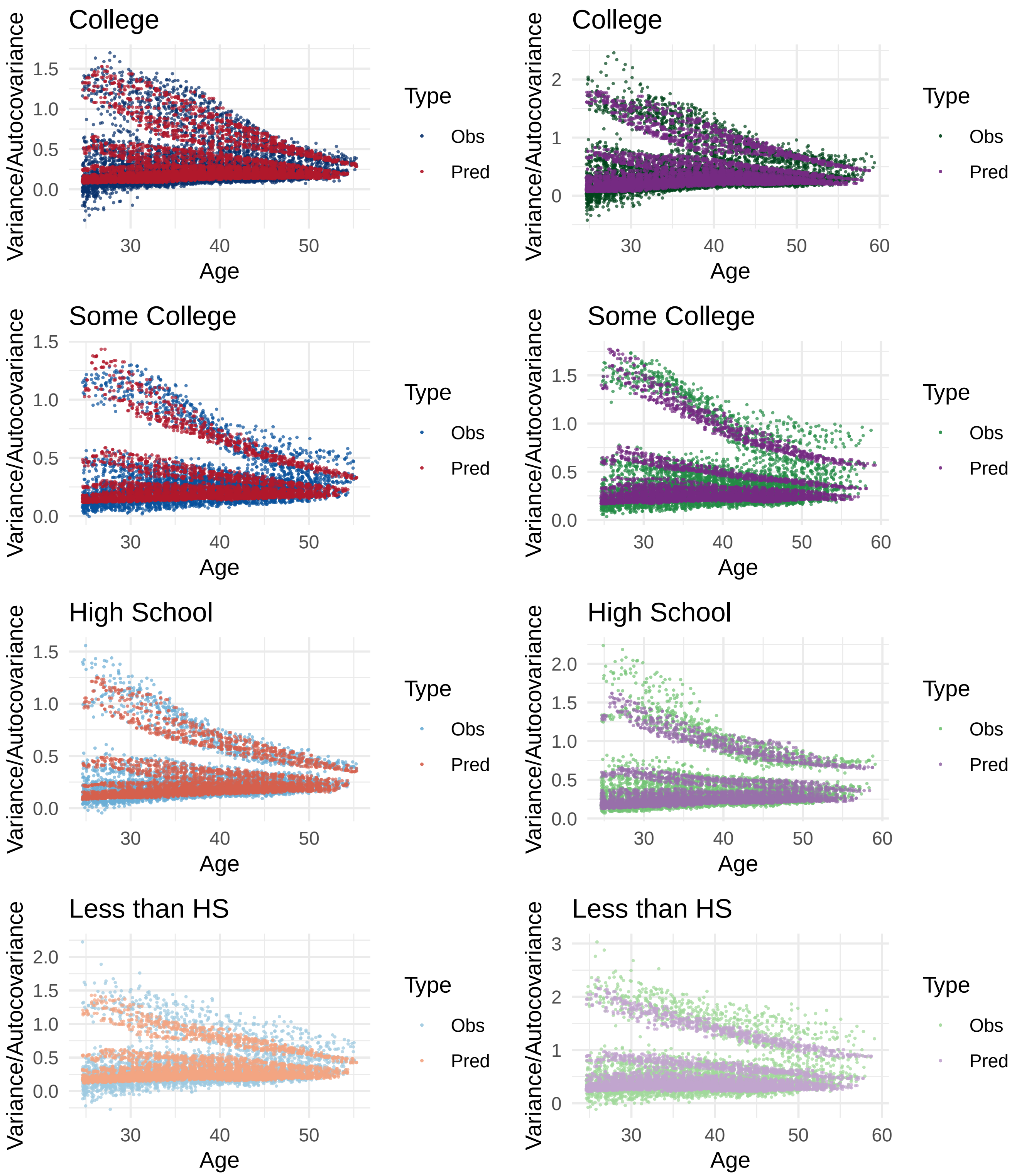

Figure 2: Predicted and observed second order moments females.
Note: Right hand column corresponds to the strict samples and the left to the lenient.

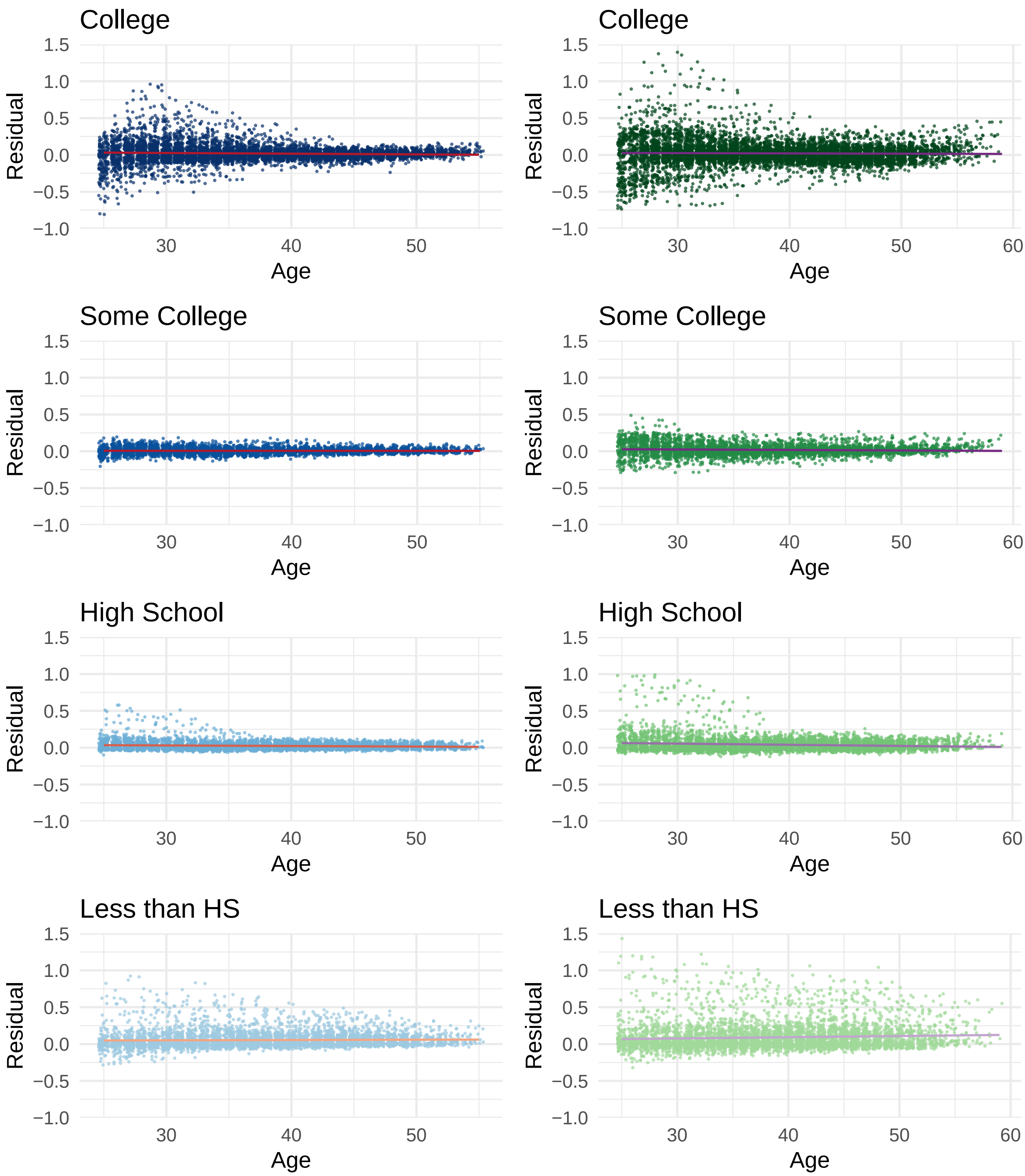

Figure 3: Residual between predicted and observed moments males.
Note: Right hand column corresponds to the strict samples and the left to the lenient.

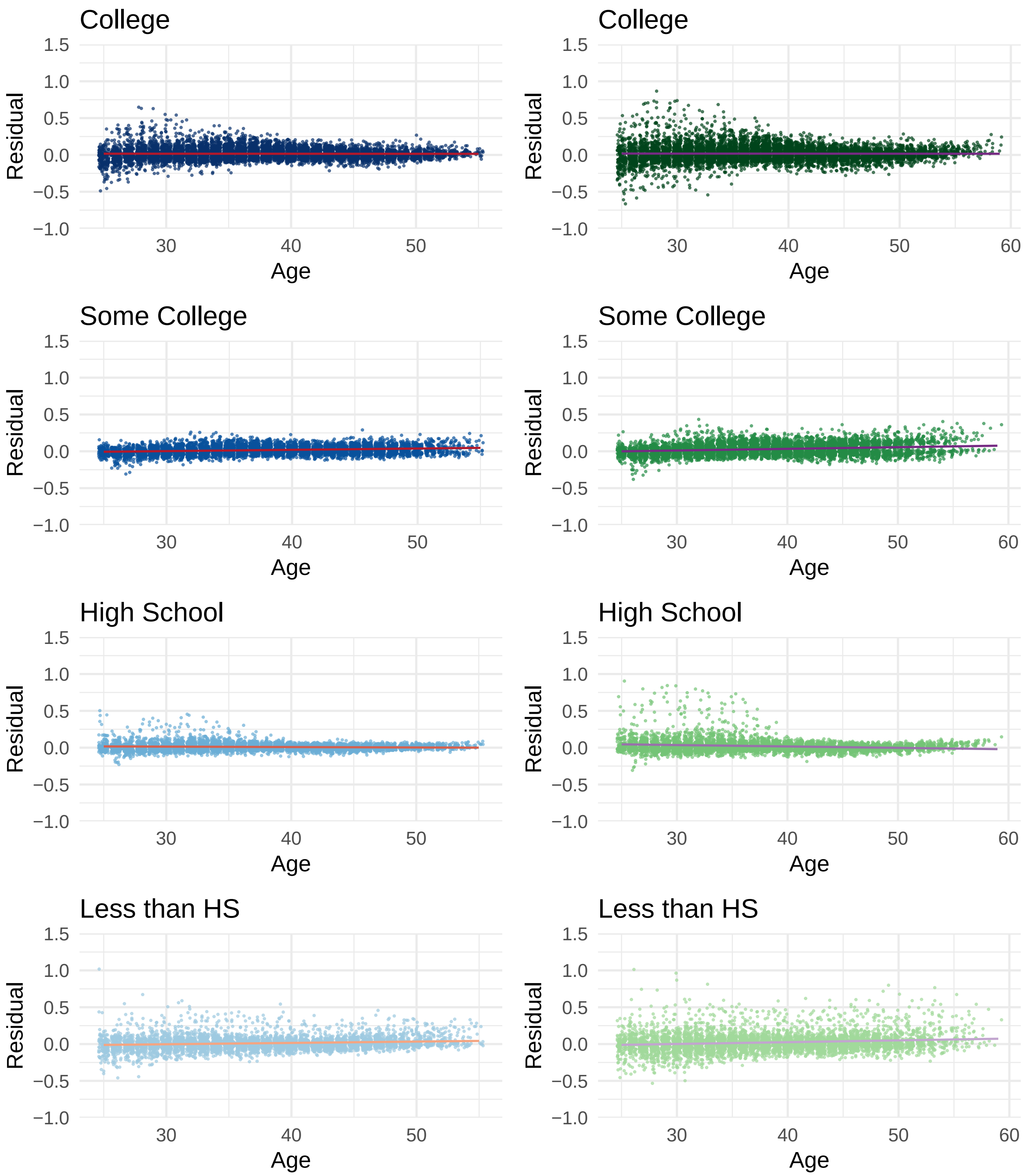

Figure 4: Residual between predicted and observed moments females.
Note: Right hand column corresponds to the strict samples and the left to the lenient.

Appendix E: Factor loadings

	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
λ_{1956}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
λ_{1957}	0.934	0.962	0.985	0.997	1.01	1	1.026	1.088
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
λ_{1958}	0.94	0.94	0.987	0.992	0.987	0.992	1.025	1.026
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1959}	0.956	0.978	0.953	0.975	0.973	0.982	1.054	1.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1960}	0.931	1.001	0.972	0.965	0.994	0.987	1.091	1.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1961}	0.997	1.044	1.038	0.976	0.975	0.994	1.06	1.06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1962}	0.962	1.033	1.018	0.954	1.025	0.999	1.036	1.047
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1963}	1.023	1	0.951	0.958	0.99	0.991	1.079	1.079
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1964}	0.971	1.036	0.926	0.9	1	0.989	1.067	1.051
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1965}	0.978	1.051	0.919	0.908	0.988	0.966	1.129	1.057
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1966}	1.004	1.132	0.895	0.939	0.952	0.947	1.054	1.016
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1967}	0.995	1.05	0.887	0.911	0.96	0.98	1.037	0.994
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1968}	1.002	1.07	0.864	0.841	1.017	0.943	0.982	0.967
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1969}	1.013	1.094	0.876	0.836	0.957	0.927	1.003	1.029
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1970}	1.009	1.063	0.869	0.844	0.959	0.922	0.991	0.947
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1971}	1.021	1.11	0.866	0.832	0.942	0.988	1.065	0.932
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1972}	1.01	1.09	0.859	0.88	0.963	0.945	0.989	0.94
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1973}	1.025	1.124	0.916	0.834	0.938	0.935	0.966	0.913

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	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1974}	1.068	1.176	0.843	0.839	0.935	0.938	1.097	1.003
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1975}	1.02	1.147	0.867	0.822	0.935	0.975	0.926	0.861
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1976}	1.122	1.243	0.837	0.802	0.867	1.001	0.851	0.847
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1977}	1.052	1.174	0.766	0.785	0.831	0.887	0.793	1.068
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1978}	0.988	1.111	0.795	0.794	0.827	0.969	1.156	1.251
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1979}	0.987	1.058	0.802	0.796	0.849	0.93	0.788	0.988
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
λ_{1980}	1.012	1.172	0.811	0.806	0.854	0.971	0.86	0.553
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
λ_{1981}	1.111	1.15	0.795	0.793	1.023	1.04	0.927	0
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(259.538)
μ_{1956}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
μ_{1957}	0.982	0.978	1.023	0.982	1.119	1.008	1.139	0.989
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
μ_{1958}	1.008	0.969	1.044	0.987	1.142	0.989	1.186	1.011
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
μ_{1959}	1.09	1.001	1.1	0.973	1.162	1	1.219	0.979
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
μ_{1960}	1.176	1.011	1.094	0.995	1.161	0.984	1.337	1.012
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
μ_{1961}	1.156	1.06	1.073	0.972	1.209	1.033	1.342	1.009
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
μ_{1962}	1.165	1.029	1.084	0.968	1.176	0.98	1.347	1.056
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
μ_{1963}	1.167	1.048	1.081	0.95	1.206	1.044	1.459	1.081
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
μ_{1964}	1.205	1.1	1.078	0.928	1.223	0.994	1.489	1.088
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
μ_{1965}	1.243	1.093	1.074	0.923	1.185	0.976	1.425	1.131
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)

Continued on next page

	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
μ_{1966}	1.268	1.121	1.092	0.92	1.207	0.964	1.472	1.102
	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
μ_{1967}	1.273	1.145	1.068	0.889	1.212	0.99	1.512	1.098
	(0.000)	(0.004)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.003)
μ_{1968}	1.384	1.215	1.109	0.931	1.25	1.04	1.603	1.144
	(0.001)	(0.005)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.003)
μ_{1969}	1.322	1.175	1.042	0.887	1.304	1.042	1.641	1.146
	(0.001)	(0.005)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
μ_{1970}	1.358	1.206	1.05	0.89	1.358	1.048	1.575	1.199
	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.003)
μ_{1971}	1.421	1.186	1.075	0.912	1.458	1.104	1.57	1.179
	(0.001)	(0.004)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)
μ_{1972}	1.335	1.196	1.095	0.903	1.415	1.129	1.707	1.204
	(0.001)	(0.005)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)
μ_{1973}	1.38	1.237	1.078	0.922	1.581	1.173	1.726	1.256
	(0.001)	(0.005)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.005)
μ_{1974}	1.457	1.273	1.193	0.948	1.627	1.26	1.744	1.266
	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.005)
μ_{1975}	1.578	1.368	1.123	0.95	1.722	1.296	1.973	1.405
	(0.002)	(0.011)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.006)
μ_{1976}	1.664	1.376	1.147	0.982	1.838	1.354	2.298	1.457
	(0.002)	(0.009)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.006)
μ_{1977}	1.634	1.365	1.262	0.946	2.109	1.458	2.486	1.538
	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.007)
μ_{1978}	1.449	1.284	1.163	0.937	2.063	1.501	2.221	1.634
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.007)
μ_{1979}	1.478	1.346	1.163	0.983	1.974	1.491	2.535	1.945
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.004)	(0.01)
μ_{1980}	1.648	1.485	1.225	1.007	1.986	1.538	2.536	2.089
	(0.002)	(0.004)	(0.000)	(0.000)	(0.001)	(0.003)	(0.004)	(0.012)
μ_{1981}	1.464	1.405	1.168	1.068	2.006	1.536	2.617	2.797
	(0.002)	(0.005)	(0.000)	(0.000)	(0.001)	(0.003)	(0.004)	(0.017)

Table 1: Cohort factor loadings for Male Samples.

Note: Standard errors are presented in brackets beneath parameter estimates.

	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
λ_{1956}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
λ_{1957}	0.947	0.937	0.967	0.975	1.017	0.998	1.034	1.034
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1958}	0.992	0.961	0.991	1.001	0.997	1.014	1.058	1.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1959}	0.984	0.935	0.993	0.991	1.007	1.045	1.068	1.055
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1960}	0.991	0.958	0.982	0.978	1.013	1.038	1.076	1.077
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1961}	0.986	0.965	1.004	0.974	1.013	1.013	1.093	1.058
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1962}	1.016	0.941	0.992	1.003	0.978	1.026	1.103	1.047
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1963}	1.089	1.038	1.024	0.993	1.029	1.075	1.104	1.134
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1964}	1.042	1.088	0.996	0.99	1.142	1.063	1.122	1.153
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1965}	1.028	1.005	0.964	0.992	1.028	1.028	1.049	1.09
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1966}	1.13	1.046	0.948	0.956	1.015	1.025	1.122	1.192
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1967}	1.035	0.986	0.942	0.936	0.98	1.043	1.09	0.993
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1968}	1.075	0.943	0.949	0.955	0.959	1.025	1.079	0.991
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1969}	1.034	1.048	1.079	0.935	0.995	1.023	1.07	1.022
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1970}	1.017	1.087	0.898	0.936	0.975	1.093	1.055	0.983
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1971}	0.999	1.003	0.896	1.018	0.954	0.96	1.009	0.909
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1972}	1.105	1.014	0.865	0.901	1.162	0.984	0.988	0.933
	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_{1973}	1.001	1.051	0.85	0.981	0.971	1.151	1.004	1.088
	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
λ_{1974}	0.988	1.119	0.867	0.872	0.956	0.988	0.967	0.88
	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
λ_{1975}	0.898	0.969	0.822	0.828	0.973	1.109	0.937	0.854
	(0.003)	(0.007)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
λ_{1976}	0.981	1.039	0.822	0.86	0.912	0.981	0.896	0.986
	(0.004)	(0.008)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
λ_{1977}	0.948	0.998	0.771	0.792	0.926	0.948	0.817	0.751
	(0.003)	(0.009)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
λ_{1978}	0.85	0.932	0.762	0.912	0.894	0.941	0.836	0.765
	(0.003)	(0.006)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
λ_{1979}	0.895	0.929	0.77	0.797	0.868	0.924	0.894	0.651
	(0.005)	(0.007)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
λ_{1980}	0.88	1.021	0.786	0.932	0.862	0.904	0.822	0.58
	(0.008)	(0.012)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
λ_{1981}	0.878	0.929	0.769	0.852	0.862	1.09	0.854	1.06
	(0.007)	(0.011)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
μ_{1956}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
μ_{1957}	1.084	1.025	1.029	0.993	1.03	0.992	1.013	0.991
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
μ_{1958}	1.081	1.04	1.047	1.006	1.076	1.044	1.105	1.071
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
μ_{1959}	1.114	1.019	1.083	1.001	1.103	0.992	1.214	1.104
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
μ_{1960}	1.247	1.104	1.122	1.012	1.21	1.046	1.281	1.087
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)
μ_{1961}	1.236	1.091	1.135	1.049	1.198	1.052	1.28	1.13
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)
μ_{1962}	1.263	1.142	1.168	1.019	1.354	1.077	1.329	1.21
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
μ_{1963}	1.249	1.113	1.215	1.033	1.303	1.083	1.377	1.195
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
μ_{1964}	1.318	1.112	1.197	1.052	1.262	1.112	1.445	1.243
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)
μ_{1965}	1.412	1.22	1.227	1.065	1.358	1.161	1.654	1.284
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)
μ_{1966}	1.357	1.171	1.321	1.084	1.435	1.215	1.52	1.285

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	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
	(0.001)	(0.003)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.002)
μ_{1967}	1.403	1.197	1.346	1.142	1.573	1.193	1.598	1.455
	(0.001)	(0.003)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
μ_{1968}	1.415	1.233	1.358	1.109	1.611	1.225	1.624	1.41
	(0.001)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
μ_{1969}	1.477	1.257	1.33	1.184	1.559	1.265	1.661	1.414
	(0.002)	(0.006)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
μ_{1970}	1.469	1.28	1.566	1.226	1.779	1.339	1.717	1.443
	(0.002)	(0.006)	(0.000)	(0.000)	(0.002)	(0.002)	(0.004)	(0.003)
μ_{1971}	1.525	1.289	1.456	1.16	1.747	1.403	1.766	1.536
	(0.002)	(0.008)	(0.000)	(0.000)	(0.002)	(0.002)	(0.004)	(0.004)
μ_{1972}	1.49	1.263	1.618	1.221	1.701	1.394	1.834	1.476
	(0.002)	(0.005)	(0.000)	(0.000)	(0.002)	(0.002)	(0.004)	(0.004)
μ_{1973}	1.613	1.332	1.609	1.266	1.792	1.396	1.767	1.456
	(0.002)	(0.008)	(0.000)	(0.000)	(0.002)	(0.001)	(0.004)	(0.004)
μ_{1974}	1.65	1.321	1.61	1.278	1.91	1.508	1.795	1.504
	(0.004)	(0.008)	(0.000)	(0.000)	(0.002)	(0.002)	(0.004)	(0.005)
μ_{1975}	1.799	1.377	1.665	1.344	1.981	1.518	1.806	1.501
	(0.004)	(0.014)	(0.000)	(0.000)	(0.002)	(0.001)	(0.004)	(0.005)
μ_{1976}	1.763	1.43	1.678	1.346	1.967	1.536	1.915	1.507
	(0.006)	(0.012)	(0.000)	(0.000)	(0.002)	(0.001)	(0.005)	(0.005)
μ_{1977}	1.728	1.42	1.747	1.362	1.984	1.573	2.009	1.663
	(0.003)	(0.009)	(0.000)	(0.000)	(0.002)	(0.001)	(0.005)	(0.005)
μ_{1978}	1.753	1.391	1.772	1.358	2.05	1.599	2.011	1.702
	(0.001)	(0.004)	(0.000)	(0.000)	(0.002)	(0.001)	(0.005)	(0.005)
μ_{1979}	1.763	1.408	1.83	1.419	2.156	1.68	2.031	1.83
	(0.002)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)	(0.005)	(0.006)
μ_{1980}	1.767	1.5	1.832	1.45	2.164	1.712	2.124	2.008
	(0.007)	(0.012)	(0.000)	(0.000)	(0.002)	(0.002)	(0.005)	(0.007)
μ_{1981}	1.809	1.58	1.908	1.518	2.2	1.737	2.142	1.94
	(0.009)	(0.012)	(0.000)	(0.001)	(0.001)	(0.002)	(0.005)	(0.007)

Table 2: Cohort factor loadings for Female Samples.

Note: Standard errors are presented in brackets beneath parameter estimates.

	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
γ_{2002}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
γ_{2003}	1.028	1.034	1.016	1.009	1.016	1.02	1.014	0.989
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2004}	1.09	1.08	1.075	1.062	1.072	1.08	1.048	1.031
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2005}	1.12	1.086	1.114	1.089	1.114	1.11	1.079	1.069
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2006}	1.191	1.131	1.144	1.116	1.145	1.138	1.08	1.092
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2007}	1.148	1.148	1.108	1.114	1.133	1.168	1.062	1.108
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2008}	1.157	1.174	1.101	1.123	1.123	1.162	1.038	1.085
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2009}	1.214	1.18	1.18	1.167	1.174	1.205	1.048	1.08
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2010}	1.194	1.171	1.174	1.155	1.178	1.19	1.027	1.064
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2011}	1.122	1.099	1.114	1.099	1.138	1.157	0.996	1.067
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2012}	1.09	1.075	1.081	1.071	1.101	1.131	0.953	1.019
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2013}	1.062	1.021	1.068	1.044	1.08	1.101	0.935	1.008
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2014}	1.027	0.981	1.042	1.026	1.06	1.09	0.905	1.004
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2015}	0.992	0.969	1.031	1.016	1.04	1.059	0.893	0.979
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2002}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
π_{2003}	0.997	1.006	0.983	0.98	0.99	0.988	0.967	0.954
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2004}	1.033	1.011	1.009	0.992	1.009	1.002	0.934	0.926
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
π_{2005}	1.019	0.985	0.974	0.95	0.953	0.949	0.859	0.846
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)

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	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
π_{2006}	0.969	0.941	0.914	0.884	0.876	0.873	0.771	0.732
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
π_{2007}	0.865	0.909	0.805	0.831	0.775	0.816	0.676	0.672
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
π_{2008}	0.797	0.853	0.745	0.795	0.718	0.77	0.619	0.642
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
π_{2009}	0.871	0.886	0.818	0.84	0.763	0.808	0.613	0.649
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
π_{2010}	0.877	0.881	0.813	0.843	0.753	0.782	0.595	0.635
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
π_{2011}	0.817	0.858	0.765	0.81	0.704	0.752	0.565	0.598
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
π_{2012}	0.808	0.886	0.761	0.837	0.675	0.768	0.537	0.577
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2013}	0.812	0.896	0.791	0.862	0.677	0.784	0.531	0.573
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2014}	0.818	0.892	0.796	0.876	0.682	0.786	0.527	0.555
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2015}	0.849	0.908	0.804	0.89	0.679	0.789	0.534	0.553
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 3: Time factor loadings for Male Samples.

Note: Standard errors are presented in brackets beneath parameter estimates.

	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
γ_{2002}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
γ_{2003}	1.037	1	1.045	1.034	1.004	1.023	1.016	1.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2004}	1.098	1.059	1.099	1.076	1.062	1.075	1.077	1.053
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2005}	1.149	1.072	1.153	1.107	1.102	1.102	1.13	1.094
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2006}	1.25	1.131	1.199	1.127	1.151	1.135	1.159	1.108
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
γ_{2007}	1.277	1.213	1.21	1.187	1.149	1.147	1.122	1.125
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2008}	1.258	1.193	1.19	1.172	1.146	1.175	1.115	1.111
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2009}	1.23	1.155	1.185	1.163	1.127	1.152	1.075	1.082
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2010}	1.201	1.114	1.163	1.136	1.11	1.118	1.046	1.054
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2011}	1.177	1.073	1.133	1.084	1.076	1.098	0.975	1.003
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2012}	1.087	1.041	1.059	1.045	1.022	1.06	0.919	0.966
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2013}	1.044	0.99	1.023	1.009	1.012	1.03	0.884	0.936
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2014}	1.018	0.958	0.993	0.973	0.992	1.018	0.857	0.914
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{2015}	0.973	0.926	0.976	0.959	0.97	1.011	0.842	0.905
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2002}	1	1	1	1	1	1	1	1
	-	-	-	-	-	-	-	-
π_{2003}	0.98	0.971	0.978	0.971	0.965	0.973	0.972	0.966
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2004}	0.984	0.957	0.962	0.959	0.954	0.964	0.95	0.948
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2005}	0.945	0.908	0.912	0.908	0.905	0.899	0.879	0.882
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2006}	0.92	0.87	0.866	0.86	0.859	0.849	0.825	0.82
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2007}	0.844	0.856	0.799	0.812	0.782	0.807	0.762	0.776
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2008}	0.813	0.856	0.754	0.795	0.751	0.79	0.731	0.756
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2009}	0.814	0.838	0.744	0.785	0.746	0.783	0.714	0.741
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2010}	0.8	0.817	0.734	0.774	0.736	0.775	0.691	0.726
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2011}	0.765	0.784	0.701	0.75	0.702	0.754	0.663	0.702

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	Less than HS		High school		Some College		College	
	Strict	Lenient	Strict	Lenient	Strict	Lenient	Strict	Lenient
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2012}	0.738	0.807	0.683	0.758	0.684	0.756	0.632	0.68
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2013}	0.745	0.823	0.678	0.765	0.681	0.77	0.616	0.67
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2014}	0.739	0.815	0.671	0.763	0.677	0.773	0.587	0.643
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
π_{2015}	0.742	0.83	0.668	0.763	0.66	0.76	0.577	0.635
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4: Time factor loadings for Female Samples.

Note: Standard errors are presented in brackets beneath parameter estimates.