Labor Income Dynamics over the Business Cycle

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Abstract: What do labor income dynamics look like over the business cycle? How does aggregate income risk change with experience and education? To what extent do taxes, transfers and the family attenuate aggregate income risk? In this paper, we use Norwegian population panel data to answer these important questions. We model the income process as a first-order quantile-autoregressive process. We let individuals with different education levels have a separate income process, and within each skill group and cohort we allow the conditional quantile functions to vary unrestrictively over time. We find that average exposure to cyclical income risk varies substantially across skill groups and over the life-cycle; our findings also suggest that the progressive nature of the Norwegian tax-transfer system as well as spouse's income play a key role in reducing aggregate income variation. We find that income dispersion is procyclical for those at the bottom, acyclical for those in the middle, and countercyclical for those at the top of the distribution of previous income, while skewness is procyclical and declines with previous income.

Keywords: Income Dynamics; Business Cycles; Skewness Risk;
JEL codes: C31, D31

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1 Introduction

The aim of this paper is to examine the distributional dynamics of labour income over the business cycle and to explore the impact of two mechanisms of attenuation or insurance to labour income shocks. The first is the tax and transfer system; the second is spouse's income. We focus on three dimensions of income: individual market income, individual disposable income, and family disposable income. Our objective is to provide a detailed picture of the dynamics of income over the business cycle, following individuals from many different cohorts over time. By linking up individuals with other family members, we are able to examine the impact of spouse's income and the role of the tax-transfer system as mechanisms to smooth shocks to individual market income.

The distributional dynamics of labor income over the business cycle are a key ingredient in models that address a number of important questions, including the distribution of the welfare costs of business cycles (Lucas (1987); Storesletten, Telmer, and Yaron (2004); Krebs (2007); De Santis (2007); Krueger, Mitman, and Perri (2016)) and the implications of cyclical income risk for aggregate output and consumption (Bayer, Luetticke, Pham-Dao, and Tjaden (2017); McKay (2017)). The conclusions reached about these questions likely depend on the specification of the labor income process used to calibrate the models. This paper attempts to contribute to this literature by developing and estimating an income process that is is consistent with a variety of evidence on income risk over the life and business cycle (Guvenen, Ozkan, and Song (2014),Guvenen, Karahan, Ozkan, and Song (2016), Arellano, Blundell, and Bonhomme (2016)).

We model the income process as a first-order quantile-autoregressive process. Modeling the conditional distribution of income has the key advantage that it represents the most comprehensive measure of income risk (under the Markov assumption). We let individuals with different education levels have a separate income process, and within each skill group and cohort we allow the conditional quantile functions to vary unrestrictively over time. This approach represents a tractable way of allowing income risk within each skill group to depend on the previous income level, calendar time and experience in a flexible way.

[TBC]

The layout of the remainder of this paper is as follows. The next Section presents our income panel data and our choice of the business cycle indicator. Section 3 describes our panel data specification for the income process and presents measures of conditional and average income uncertainty and skewness. Section 4 presents the main empirical results. Section 5 analyses the distribution of the welfare costs of business cycles, and Section 6 concludes.

2 Data Description

2.1 Norwegian Registry Data

The empirical analysis employs several registry databases maintained by Statistics Norway that we can link through unique identifiers for each individual. This allows us to construct a rich longitudinal data set containing individual records for the entire resident population of Norway from 1979 to 2013. The panel data set contains individual demographic information (including gender, date of birth, marital status, family size and composition), socio-economic data (including income from various sources and education), and exact geographical identifiers. The data also contains unique family identifiers that enable us to measure income at the household level by matching individuals with their spouses, and parents to their children.

Registry data are ideal for our purpose of studying income dynamics, in particular because of the long time dimension and the large number of cross-sectional observations. Furthermore, the coverage and reliability of Norwegian registry data are considered to be outstanding (Atkinson, Rainwater, and Smeeding (1995)). There is no attrition from the original sample because of the need to ask for permission from individuals to access their tax records. In Norway, these records are in the public domain. The income data also pertain to all individuals and all jobs, and not only to jobs covered by social security and measures of incomes are recorded without any top- or bottom coding. In addition, there are little reporting or recollection errors, which is a common problem with survey-based micro datasets. The income data come from individual tax records with detailed information about the different sources of income, while educational attainment is reported by the educational establishments directly to Statistics Norway.

The income variables that we consider are defined as follows. The first variable is annual *individual market income*. This includes all income received as a worker during a given calendar year, including acquired benefits during unemployment, sickness allowance and maternity/paternity leave benefits. The second variable is *individual disposable income* measured as individual market income plus cash transfers net of taxes on earnings.[1] The third income variable is *family disposable income*, defined as the sum of the individual disposable income of the spouses. Throughout the empirical analysis we treat cohabiting couples identical to married couples.[2] Finally, all income measures are deflated to the base year 2005 using the Consumer Price Index (CPI) provided by Statistics Norway and converted to US Dollars by using the average of the daily exchange rates in 2005.[3]

[1] As seems appropriate in this context, this income measure does not include income from financial assets. In every year, we compute taxes using a tax simulation program available at Statistics Norway.

[2] Cohabitants are identified from the National Censuses of Population and Housing in 1980 and 2001, and the National Survey of Population and Housing in 1990, as well as from Statistics Norway's own datasets identifying cohabiting couples after 2004. Further, cohabiting couples are roughly identified from annual registry data as men and women living at the same address who at some point have children together or become cohabitating couples, or who get married at a later point in time.

[3] The CPI is available here: http://www.ssb.no/en/inntekt-og-forbruk. The daily exchange rates between USD and NOK are available here: http://www.norges-bank.no/en/Statistics/exchange_rates/. The average daily exchange rate (NOK/USD) in 2005 was 6.4450.

The life cycle is measured by *potential labor market experience*, defined as age minus years of education minus 6. To minimize the impact of heterogeneity in the initial transition from education to the labor market, we focus on the range of potential experience from 4 to 40 throughout the empirical analysis. We define a *cohort* as a group of individuals that have completed education in a given year.

Throughout the empirical analysis we focus on households with a male earner as household head. In every year, we restrict the panel to include non-immigrant men and their spouse (if they have one) who filed a tax return and who have non-missing information on key demographic characteristics. To ensure fairly long records on earnings for each individual, we focus on cohorts that enter the labour market between 1950 and 2005. In line with much of the previous literature on income dynamics, we exclude individuals whose primary source of income comes from self-employment. We also exclude observations in a given year if they fall below a time-varying minimum threshold. This minimum threshold is taken to be 0.1 basic amounts, which amounts to roughly 1,300 USD in 2013.[4] Such a minimum threshold condition is fairly standard in the income dynamics literature and ensures that we select individuals with a reasonably strong labor market attachment.[5]

Applying these restrictions leaves us with an unbalanced panel of 27,272,712 household-year observations. To account for heterogeneity by educational attainment, we partition the sample into three mutually exclusive groups according to educational levels of the household head. Low skilled is defined as not having completed high school (20% of the sample), medium skilled includes those with a high school degree (52% of the sample), and the high skilled consists of those who have attended college (29% of the sample). Table 1 displays some summary statistics for the three subsamples and Appendix Figure 4 graphs the average log income over the life cycle.

[4]One basic amount is the so called threshold of substantial gainful activity. The nominal level of the threshold varies year-by-year according to the development of wages in the Norwegian economy.

[5]From a technical perspective a minimum threshold also sidesteps the issue of taking the logarithm of small numbers.

variable	N	Mean	Std. Dev.	10pctile	25pctile	Median	75pctile	90pctile
age	5,377,227	36.27	9.87	23.00	28.00	36.00	44.00	50.00
p. experience	5,377,227	20.62	10.21	7.00	12.00	20.00	29.00	35.00
married	5,377,227	0.40	0.49	0.00	0.00	0.00	1.00	1.00
children	5,377,227	0.96	1.14	0.00	0.00	1.00	2.00	3.00
market income	5,377,227	40,348.74	22,613.57	13,191.46	28,731.58	39,192.58	50,131.80	63,967.12
disposable income	5,377,227	28,629.56	13,304.12	13,336.87	21,699.78	27,449.69	34,757.82	43,719.57
family disposable income	5,377,227	36,947.15	20,783.43	14,363.49	23,244.61	33,395.98	47,234.95	63,629.99

(a) Low-skilled

variable	N	Mean	Std. Dev.	10pctile	25pctile	Median	75pctile	90pctile
age	14,106,136	38.94	9.81	26.00	31.00	38.00	47.00	53.00
p. experience	14,106,136	20.35	10.00	7.00	12.00	20.00	28.00	35.00
married	14,106,136	0.53	0.50	0.00	0.00	1.00	1.00	1.00
children	14,106,136	1.07	1.14	0.00	0.00	1.00	2.00	3.00
market income	14,106,136	52,115.60	28,691.23	27,126.93	37,740.87	47,904.05	61,733.43	80,657.37
disposable income	14,106,136	35,038.03	15,862.77	20,855.57	26,204.25	32,488.98	41,371.34	52,342.48
family disposable income	14,106,136	47,165.48	24,072.34	22,758.58	30,771.19	42,853.25	59,133.27	78,108.02

(b) Medium-skilled

variable	N	Mean	Std. Dev.	10pctile	25pctile	Median	75pctile	90pctile
age	7,789,349	41.55	9.94	29.00	33.00	40.00	49.00	56.00
p. experience	7,789,349	19.00	9.87	6.00	11.00	18.00	27.00	34.00
married	7,789,349	0.62	0.49	0.00	0.00	1.00	1.00	1.00
children	7,789,349	1.13	1.16	0.00	0.00	1.00	2.00	3.00
market income	7,789,349	69,530.29	50,329.06	33,259.02	46,711.06	60,742.78	82,063.64	112,832.84
disposable income	7,789,349	43,888.58	26,645.44	23,984.41	30,721.20	39,220.31	51,645.95	68,881.73
family disposable income	7,789,349	61,405.41	36,076.08	27,278.28	38,646.39	55,275.75	77,351.39	102,316.48

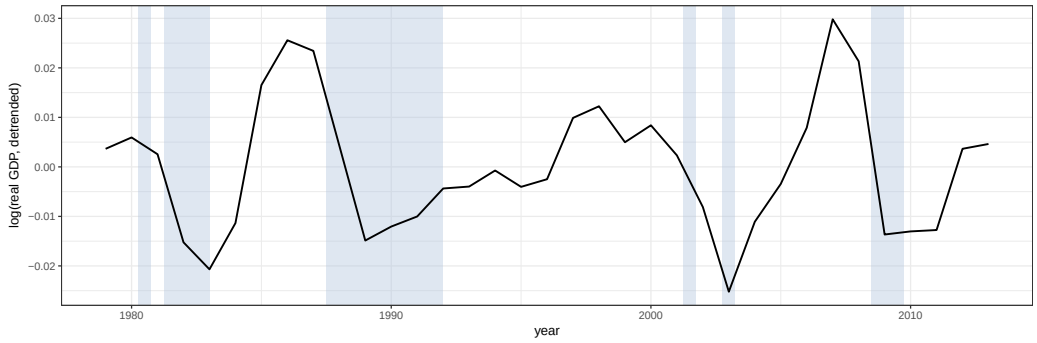
(c) High-skilled

Table 1: Summary Statistics

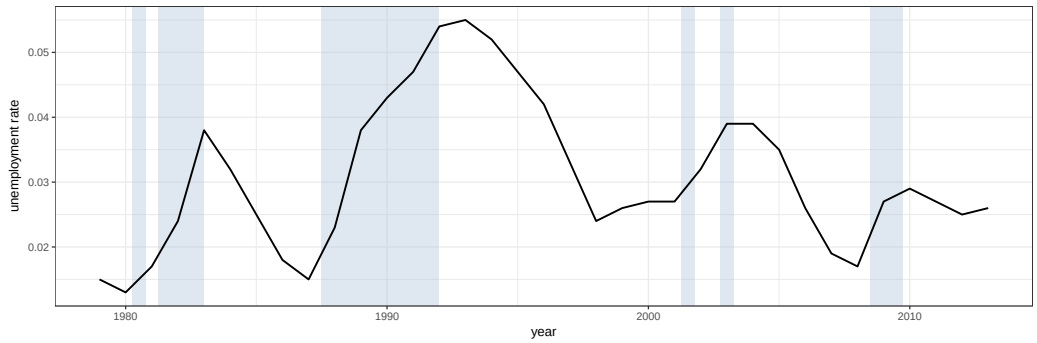
Notes: This table shows summary statistics of key variables by educational levels. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

2.2 Business Cycle Conditions

The primary business cycle indicator used in this chapter is the annual real Gross Domestic Product (GDP) of mainland Norway.[6] To capture the business cycle, we apply a Hodrick-Prescott filter to the natural logarithm of annual real GDP of mainland Norway, using a smoothing parameter of 6.25 for annual data as suggested by Ravn and Uhlig (2002). Hence the business cycle conditions are expressed in terms of the log deviation of the real GDP from its trend. For robustness checks, I consider the the annual unemployment rate as an alternative business cycle indicator.[7] Figure (1) shows the evolution of the two business cycle indicators over time.[8]



(a) HP-filtered natural logarithm of annual real GDP



(b) Unemployment rate

Figure 1: Business cycle indicators

Notes: This figure shows the evolution of business cycle indicators over time. Panel (a) shows the time-series of the HP-filtered natural logarithms of annual real GDP. Panel (b) shows the time-series of the unemployment rate. The grey bars indicate recessions in Norway as dated by Aastveit, Jore, and Ravazzolo (2016) according to their preferred method (MS-FMQ).

The Norwegian economy experienced 6 recessions (peak to trough) over the sample

[6]The GDP series relates to mainland Norway and therefore excludes offshore acitivity, namely oil and gas extraction and international shipping. The main reason for the exclusion of these sectors is the fact that their production may show large fluctuations that have very small short term effects on the Norwegian labor market (see Aastveit, Jore, and Ravazzolo (2016)).

[7]The time-series for the unemployment rate is published by the Norwegian Labour and Welfare Administration and are available to download from https://www.nav.no/no/NAV+og+samfunn/Statistikk/Arbeidssokere+og+stillinger+-+statistikk/Historisk+statistikk.

[8]The cross-correlation between the two time-series over the sample period is −0.55.

period (see Aastveit, Jore, and Ravazzolo (2016)).[9] Norway experienced a double-dip recession at the beginning of the 1980s, followed by a deep and long-lasting recession at the end of the 1980s. This particular recession turned into a banking crisis that was accompanied by a large increase in the unemployment rate by 4 percentage points until the early 1990s. The early 2000s were characterised by two relatively short-lived recessions. Finally, the Great Recession had a relatively moderate impact on the Norwegian labour market with an already relatively low unemployment rate raising raising by only 1.2 percentage points.

3 Empirical Approach

3.1 The Income Process

Following the mainstream approach in the income dynamics literature, we decompose log income of household i in year t into two components,

$$\ln Y_{it} = f_t(X_{it}) + y_{it}. \tag{1}$$

The component $f_t(X_{it})$ is a function that depends on calendar time t and on observable household characteristics X_{it}, and y_{it} represents the idiosyncratic component of income.

Aggregate Variation in Income. The first component of decomposition (1) captures the deterministic cross-sectional variation in income attributable to observable household characteristics such as marital status, household size, region of residence, potential experience and cohort. Aggregate variation in log income is captured by the functional dependence on calendar time. Ideally one would like to control for the effects from potential experience (h), cohort (c) and calendar time (t) in an unrestricted way. Recall, however, that we have defined a cohort as a group of individuals who have completed education in a given year, so that potential experience, year and cohort are perfectly collinear, i.e. $c = t - h$. Thus the level effects of these three factors cannot be separately identified.[10]

An extent literature has pointed out several ways to deal with this fundamental identification problem. The standard approach involves imposing one or more restrictions. Deaton (1997) for example suggests a normalisation that makes the year effects average to zero over the sample period and be orthogonal to a time trend, such that all growth is attributed to experience and cohort effects. Another widespread approach is to assume that either cohort or time effects are zero, so that secular trends appear only in time or cohort effects respectively.[11] We follow an approach suggested by Heckman and Robb (1985) instead.

[9] Note that there is no authoritative dating of business cycles for the Norwegian economy. Aastveit, Jore, and Ravazzolo (2016) provide dates of business cycles according to 4 different methods. We follow here their preferred method (MS-FMQ) and date business cycles according to Table 1 in their paper.

[10] Even if we were to define cohort by the year of birth, we would still have to deal with a substantial problem of multicollinearity.

[11] As highlighted by Heathcote, Storesletten, and Violante (2005), the age profiles of inequality can look very different depending on whether one assumes cohort or time effects to be at work. In a recent paper,

The general idea is to treat experience, cohort and time effects as proxy variables for underlying variables which are not themselves linearly dependent. Hence we interpret time effects as proxy variables for underlying aggregate economic conditions that in principle can be measured by business cycle indicators. Conveniently, this approach allows us to measure the average cyclical variation of log income. Hence we specify

$$f_t(X_{it}) = x'_{it}\varphi + \psi_h + \lambda_c + \xi \ln Z_t, \tag{2}$$

where ψ_h and λ_c denote experience and cohort fixed effects, and x_{it} captures the deterministic income effects attributable to household size, marital status and region. Of particular interest in the context of our analysis is the coefficient ξ which measures the average elasticity of income with respect to the contemporaneous cyclical conditions Z_t. To allow for the possibility that the cyclicality of income changes over the life cycle, we implement an alternative specification,

$$f_t(X_{it}) = x'_{it}\varphi + \psi_h + \lambda_c + \sum_h \xi_h \mathbb{1}_h \ln Z_t, \tag{3}$$

where $\mathbb{1}_h$ is an indicator variable that takes on the value one if the individual has potential experience h. The series $\{\xi_h\}$ measures the average elasticity of income with respect to the contemporaneous cyclical conditions at any stage in the life cycle.

Dynamics of Residual Income. We now shift attention to the dynamics of the idiosyncratic income component y_{it}. Motivated by the quantile-based framework recently proposed by Arellano, Blundell, and Bonhomme (2016), we model its law of motion as a first-order quantile autoregressive process. For *a given cohort* of households, the idiosyncratic income is assumed to evolve over time according to

$$y_{it} = Q_t(y_{i,t-1}, u_{it}), \tag{4}$$

where $Q_t(y_{i,t-1}, \tau)$ denotes the τ-th conditional quantile of y_{it} given $y_{i,t-1}$. The innovation u_{it} given $y_{i,t-1}, ..., y_{i,1}$ is uniformly distributed on the unit interval, and the distribution of the initial condition $y_{i,1}$ is left unrestricted.

Some discussion of our modeling choice is warranted. In contrast to Arellano et al. (2016), we do not retain the typical permanent-transitory framework and instead restrict ourselves to a single-error formulation. This choice is made solely for computational reasons in view of the large sample size we are dealing with in the estimation. Provided that we have estimates for the idiosyncratic income component, a single-error formulation has the advantage that the estimation only involves a series of quantile-autoregressions as opposed to an iterative estimation procedure as in Arellano et al. (2016). Considering also that a transitory income component often represents a mixture of transitory income shocks and

Schulhofer-Wohl (2013) proposes an estimation method for structural life cycle models that avoids the documented problems of the standard approach.

measurement error, we hope that the single-error formulation is less problematic in the presence of high-quality administrative data.

As highlighted by Arellano et al. (2016), nonlinearities in the persistence of the income process are a key feature of the nonlinear income process (4). In this framework, the partial derivative of the τ-th conditional quantile function,

$$\rho_t(\tau, y_{i,t-1}) = \frac{\partial Q_t(y_{i,t-1}, \tau)}{\partial y_{i,t-1}}, \tag{5}$$

measures the persistence of $y_{i,t-1}$ when the process is hit by a shock $u_{i,t}$ that has rank τ. This allows for the possibility that both the rank of the income shock as well as the household's current position in the income distribution can affect the persistence of $y_{i,t-1}$ in rather general ways. Allowing for nonlinear persistence, as highlighted by these authors, is key to capture empirically the effects of a variety of income shocks. Appendix Figures (5) - (8) show that nonlinear persistence is a key feature of the data, and that average persistence varies systematically over the life cycle. Our empirical results, however, suggest that persistence does not appear to change over the business cycle in any systematic and economically relevant way. For the rest of the paper, we therefore abstract from analysing it in more detail.

3.2 Conditional Uncertainty and Skewness

A key advantage of the quantile autoregressive process (4) is that it allows us to characterise any quantile of the conditional distribution. Clearly, the conditional distribution as a whole is the most comprehensive measure of income risk. It combines all aspects of income uncertainty by its nature. In the interest of an insightful empirical analysis, however, we restrict ourselves to a few characteristics of the conditional distribution. In line with the recent literature on income risk over the business cycle (e.g. Guvenen, Ozkan, and Song (2014)), we focus on two key characteristics of a distribution: dispersion and asymmetry.

Typically, the dispersion of a distribution is measured by its standard deviation. A corresponding quantile-based measure for some $\tau \in (0.5, 1)$ is

$$\sigma_t(y_{i,t-1}, \tau) = Q_t(y_{i,t-1}, \tau) - Q_t(y_{i,t-1}, 1-\tau). \tag{6}$$

From the perspective of household i in period $t-1$, the measure $\sigma_t(y_{i,t-1}, 0.75)$ represents the interquartile range of the household's possible (residual) income realisations one period ahead in t. Put differently, it measures the width of the range which holds 50% of the household's (residual) income next period and as such can be interpreted as a measure of conditional income uncertainty. Average income uncertainty is given by

$$\bar{\sigma}_t(\tau) = \mathbb{E}\left[Q_t(y_{i,t-1}, \tau) - Q_t(y_{i,t-1}, 1-\tau)\right], \tag{7}$$

where the expectation is taken with respect to the distribution of $y_{i,t-1}$.

The degree of asymmetry of a distribution is measured by its skewness. For some

$\tau \in (0.5, 1)$, a quantile-based measure of conditional skewness is

$$\gamma_t(y_{i,t-1}, \tau) = \frac{Q_t(y_{i,t-1}, \tau) + Q_t(y_{i,t-1}, 1-\tau) - 2Q_t(y_{i,t-1}, 0.5)}{Q_t(y_{i,t-1}, \tau) - Q_t(y_{i,t-1}, 1-\tau)}, \tag{8}$$

and its average is given by

$$\bar{\gamma}_t(\tau) = \mathbb{E}\left[\frac{Q_t(y_{i,t-1}, \tau) + Q_t(y_{i,t-1}, 1-\tau) - 2Q_t(y_{i,t-1}, 0.5)}{Q_t(y_{i,t-1}, \tau) - Q_t(y_{i,t-1}, 1-\tau)}\right]. \tag{9}$$

For the interpretation of some of the empirical results discussed further below, it is useful to note the link between the conditional measure of dispersion and skewness. Rearranging (8) yields,

$$\frac{Q_t(y_{i,t-1}, \tau) - Q_t(y_{i,t-1}, 0.5)}{\sigma_t(y_{i,t-1}, \tau)} = \frac{\gamma_t(y_{i,t-1}, \tau) + 1}{2}, \tag{10}$$

which implies that less than half of the overall dispersion is explained by the length of the upper tail if the distribution is skewed to the left ($\gamma_t(y_{i,t-1}, \tau) < 0$).

3.3 Empirical Implementation

The estimation strategy involves two steps. In the first step, we estimate the income process (1) by pooled OLS separately for each skill group and for each income measure, using log deviations of real GDP from its trend as business cycle indicator. In the second step, we then work with the residuals from these regressions, $y_{i,t} \equiv \ln Y_{i,t} - \hat{f}_t(X_{it})$, where $f_t(.)$ is specified according to (3).

For the empirical implementation of (4), we need a flexible, yet parsimonious specification of a continuous function. A straightforward way to approximate a continuous and smooth function is accomplished by the use of orthogonal polynomials (see for example Judd (1998), ch. 6). For each cohort and time period, we specify the τ-th conditional quantile function as,

$$Q_t(y_{i,t-1}, \tau) = \sum_{k=0}^{4} \kappa_{t,k}(\tau) H_k(y_{i,t-1}), \tag{11}$$

where $H_k(.)$ denotes the Hermite polynomial of degree k and $\kappa_{t,k}(\tau)$ denotes its corresponding polynomial coefficient. For any given cohort and year, we obtain the polynomial coefficients corresponding to any given $\tau \in (0, 1)$ by quantile-autoregression. Based on these estimates, we calculate the corresponding time and cohort specific measure of dispersion and skewness, where we evaluate expressions (6) and (8) at values of lagged income corresponding to selected percentiles of the distribution income in the previous period.

Note that for any given cohort, the τ-th conditional quantile function (4) is allowed to vary with time, and thus, experience in an unrestricted way. In other words, we allow for unrestricted variation in the conditional quantile function over time, experience and across cohorts. The same applies to the measures of uncertainty and skewness by construction. Of course, and as already pointed out in Section 3.1, not all three effects can be identified without additional restrictions.

As before, we interpret time effects as proxy variables for underlying aggregate economic conditions that are measured by business cycle indicators (Heckman and Robb (1985)). Specifically, we calculate correlations between the various measures of conditional uncertainty and skewness, and the change in the business cycle indicator, whilst controlling for potential experience and cohort effects. To fix ideas, consider the following regression framework:

$$m_{ct} = \alpha + \psi_h + \lambda_c + \xi \Delta \ln Z_t + \varepsilon_{ct}, \tag{12}$$

where ψ_h and λ_c denote experience and cohort fixed effects respectively. The dependent variable m_{ct} corresponds to one of the cohort and time specific estimates of conditional or average dispersion and skewness. The coefficients ξ then capture the cyclicality of theses measures, while the coefficients on the experience dummies trace out the average life cycle profiles.

To calculate confidence intervals, we apply a block bootstrap procedure in which we resample households, but take the residuals from the first stage as given. Sampling at the household level ensures that the autocorrelation structure from the original sample is preserved.

4 Main Results

4.1 Aggregate Variation in Income

I estimate the income process (1) together with specification (2) and (3) by pooled OLS separately for each skill group and for each income measure, using log deviations of real GDP from its trend as business cycle indicator. Table 2 reports the results of these regressions.

The results reported in columns (1) represent the estimates for specification (2). For each skill group, I find that individual market income is more cyclical than individual disposable income, which in turn appears to be more cyclical than family disposable income. For instance, a one-percent negative deviation of GDP from its trend implies that market income for low-skilled males is reduced by around 1.44% on average. This is in contrast to around 1.14% for individual disposable income and 1.08% for family disposable income. Another key finding is that, low-skilled households have the largest exposure to aggregate cyclical income risk, while high-skilled households are the least exposed to cyclical fluctuations. For example, high skilled households experience on average a 0.51% drop in their family disposable income in response to a one percent deviation of GDP from its trend. The corresponding number for medium skilled households is 0.81% and 1.08% for the low skilled. Taken together, these results suggest that (i) the cyclicality of income varies substantially across skill groups, and (ii) the tax-transfer system as well as spouse's income play an important role in reducing aggregate income variation.

We now shift attention to the results of specification (3) presented in columns (2). We find that income is more cyclical for workers early in their careers. For example, a one-percent negative deviation of GDP from its trend implies on average a reduction of around

	market income		disposable income		family disposable income	
	(1)	(2)	(1)	(2)	(1)	(2)
ln(real GDP, det.)	1.438***		1.142***		1.080***	
	(0.019)		(0.014)		(0.014)	
𝟙{exp.=5}×ln(real GDP, det.)		3.560***		2.789***		2.804***
		(0.144)		(0.118)		(0.117)
𝟙{exp.=10}×ln(real GDP, det.)		1.925***		1.330***		1.210***
		(0.110)		(0.086)		(0.084)
𝟙{exp.=20}×ln(real GDP, det.)		1.267***		0.976***		1.005***
		(0.111)		(0.080)		(0.075)
𝟙{exp.=30}×ln(real GDP, det.)		0.977***		0.788***		0.718***
		(0.100)		(0.065)		(0.058)
𝟙{exp.=40}×ln(real GDP, det.)		1.021***		1.086***		0.959***
		(0.201)		(0.103)		(0.092)
R^2	0.16	0.16	0.26	0.26	0.49	0.49
Num. Obs.	5,377,227	5,377,227	5,377,227	5,377,227	5,377,227	5,377,227

(a) low-skilled

	market income		disposable income		family disposable income	
	(1)	(2)	(1)	(2)	(1)	(2)
ln(real GDP, det.)	1.127***		0.880***		0.814***	
	(0.009)		(0.007)		(0.006)	
𝟙{exp.=5}×ln(real GDP, det.)		2.280***		1.697***		1.671***
		(0.075)		(0.060)		(0.059)
𝟙{exp.=10}×ln(real GDP, det.)		1.317***		0.952***		0.871***
		(0.054)		(0.040)		(0.039)
𝟙{exp.=20}×ln(real GDP, det.)		1.224***		0.888***		0.793***
		(0.047)		(0.034)		(0.030)
𝟙{exp.=30}×ln(real GDP, det.)		0.699***		0.613***		0.573***
		(0.057)		(0.039)		(0.034)
𝟙{exp.=40}×ln(real GDP, det.)		0.867***		0.837***		0.762***
		(0.103)		(0.062)		(0.051)
R^2	0.17	0.17	0.28	0.28	0.54	0.54
Num. Obs.	14,106,136	14,106,136	14,106,136	14,106,136	14,106,136	14,106,136

(b) medium-skilled

	market income		disposable income		family disposable income	
	(1)	(2)	(1)	(2)	(1)	(2)
ln(real GDP, det.)	0.815***		0.542***		0.505***	
	(0.013)		(0.010)		(0.009)	
𝟙{exp.=5}×ln(real GDP, det.)		1.963***		1.492***		1.368***
		(0.097)		(0.080)		(0.077)
𝟙{exp.=10}×ln(real GDP, det.)		0.836***		0.514***		0.421***
		(0.061)		(0.049)		(0.046)
𝟙{exp.=20}×ln(real GDP, det.)		0.870***		0.483***		0.446***
		(0.060)		(0.045)		(0.042)
𝟙{exp.=30}×ln(real GDP, det.)		0.377***		0.320***		0.268***
		(0.073)		(0.058)		(0.049)
𝟙{exp.=40}×ln(real GDP, det.)		-0.376		−0.487**		−0.159
		(0.224)		(0.062)		(0.133)
R^2	0.22	0.22	0.30	0.30	0.55	0.55
Num. Obs.	7,789,349	7,789,349	7,789,349	7,789,349	7,789,349	7,789,349

(c) high-skilled

Table 2: Aggregate variation in income

Notes: This table present coefficients of pooled OLS regressions. The results from specifications (2) and (3) are presented in column (1) and (2) respectively. The business cycle indicator is the HP-filtered natural logarithm of real GDP of mainland Norway. Other controls include potential experience fixed effects, cohort fixed effects, region fixed effects, a dummy for marital status and dummies for the number of children in the household. Standard errors are presented in parentheses, and are clustered at the individual-level. ***, **, and *, represent statistical significance at 0.1%, 1%, and 5% levels, respectively.

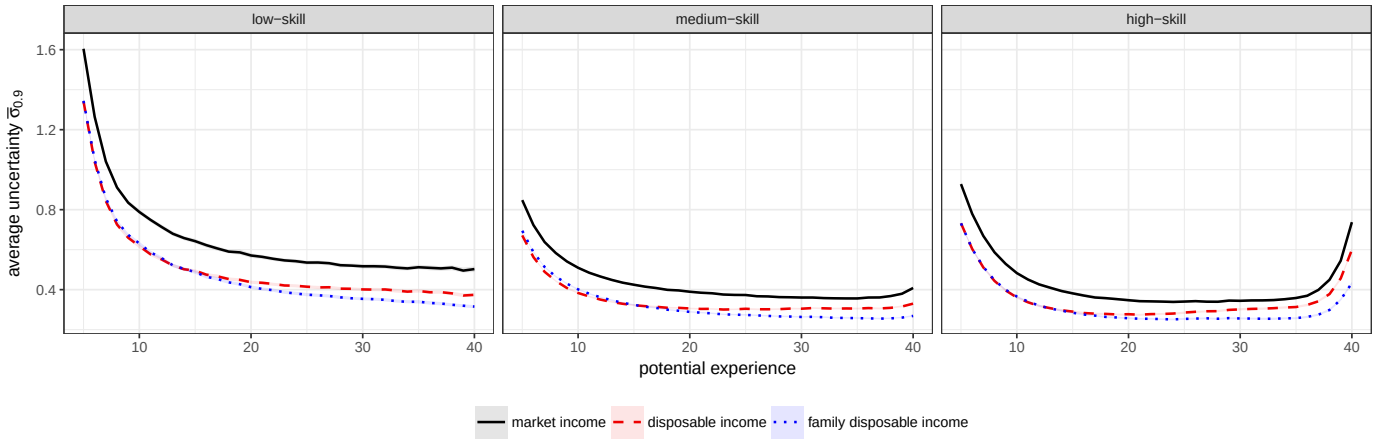
3.56% in market income among low skilled males five years after leaving education. Twenty and thirty years after having completed education, this number is reduced to around 1.27% and 0.98% repectively. It is only at the very end of the working life, where income becomes more cyclical again. With forty years of potential experience, the average elasticity amounts to 1.02. Generally, the cyclicality of income of exhibits a U-shape for both low- and medium skilled households, whereas for high skilled it appears to be monotonically decreasing with experience. The same life cycle pattern is also observed after accounting for taxes and transfers and the income of the spouse. These results suggest that the average exposure to cyclical risk differs substantially across different points in the life cycle, with younger individuals experiencing a more cyclical income stream.

Finally, I examine whether the previous results remain economically and statistically significant if I use the demeaned unemployment rate as business cycle indicator. I also investigate whether including individual fixed effects instead of cohort fixed effects significantly changes the previous results. The prior results remain robust against these different specifications and are reported in Appendix Table 5 and Appendix Table 6 respectively.

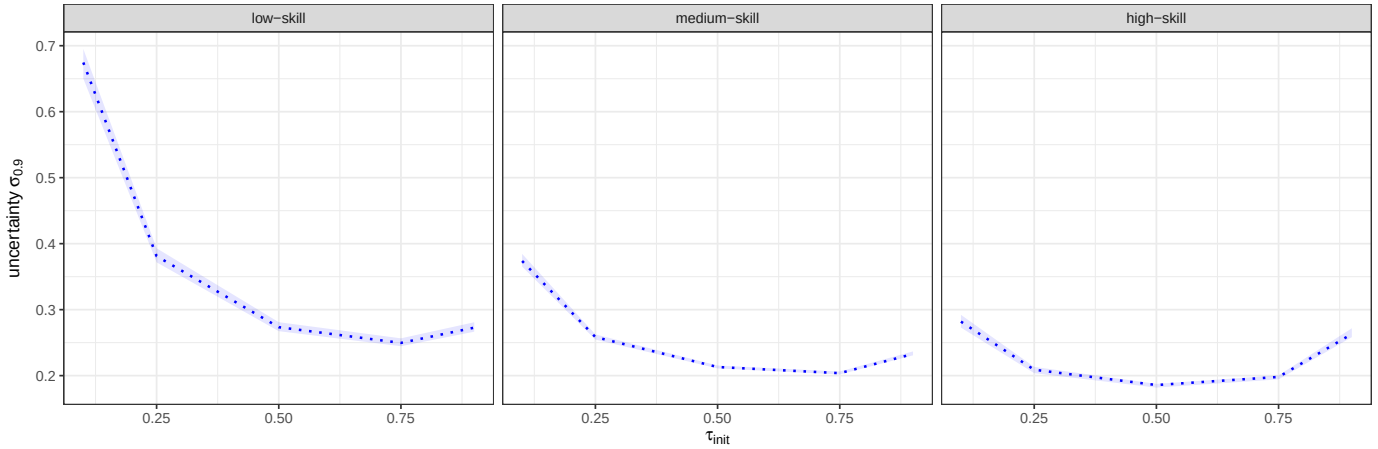
4.2 Idiosyncratic Income Risk

In this section we investigate the distributional dynamics of (residual) income over the life and business cycle.

Figure (2a) shows the estimated life cycle profiles of average income dispersion, defined in (7) and evaluated at $\tau = 0.9$. We find that the magnitude of income dispersion varies systematically with potential experience and across skill groups. Households are exposed to a substantial amount of income uncertainty early in their careers. We also observe that at almost any stage in the life-cycle the low skilled are exposed to more income uncertainty than the medium skilled, who in turn face more uncertainty than the high skilled. A comparison across the different measures of income reveals that the tax- and transfer system leads to a remarkable compression of incomes. A pooling of resources at the household level leads to a further reduction in dispersion after around 20 years of potential experience. These results suggest the tax- and transfer system and the family provide a significant amount of insurance against income shocks.



(a) Average dispersion over the life cycle



(b) Conditional dispersion in family disposable income

Figure 2: Average and conditional dispersion

Notes: This figure shows (a) the life cycle profile of the average dispersion, defined in (7) with $\tau = 0.9$, (b) conditional dispersion in family disposable income, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; 20 years of potential experience. The estimates are net of cohort and business cyle effects based on model (12). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (11), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δln(real GDP, det.), standardised	0.0092*	−0.0001	−0.0082*	0.0124*	0.0002	−0.0047*	0.0091*	0.0003	−0.0045*
	(0.0018)	(0.0005)	(0.0006)	(0.0013)	(0.0004)	(0.0005)	(0.0012)	(0.0004)	(0.0005)

(a) low-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δln(real GDP, det.), standardised	0.0094*	−0.0020*	−0.0073*	0.0110*	−0.0011*	−0.0047*	0.0093*	−0.0006*	−0.0040*
	(0.0007)	(0.0002)	(0.0003)	(0.005)	(0.0002)	(0.0002)	(0.0005)	(0.0001)	(0.0002)

(b) medium-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δln(real GDP, det.), standardised	0.0025*	−0.0019*	−0.0042*	0.0047*	−0.0012*	−0.0039*	0.0046*	−0.0010*	−0.0031*
	(0.0009)	(0.0003)	(0.0004)	(0.0006)	(0.0002)	(0.0003)	(0.0005)	(0.0002)	(0.0003)

(c) high-skilled

Table 3: Cyclicality of conditional dispersion

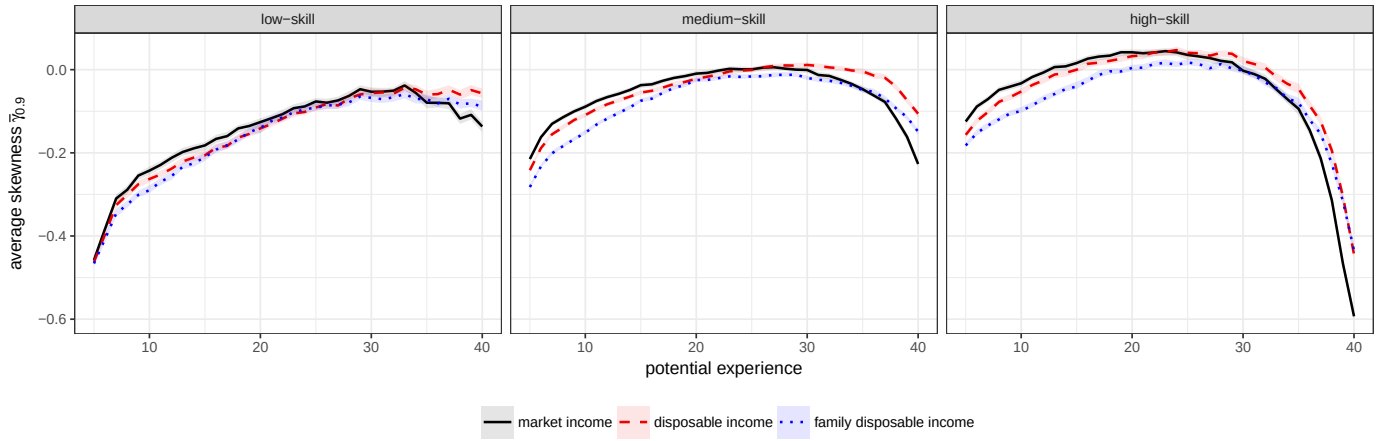
Notes: This table presents the results of model (12). Cyclicality is captured by the coefficient on the change in HP-filtered log real GDP of mainland Norway, normalised to have mean zero and unit standard deviation. The dependent variables are the cohort and time specific measures of conditional dispersion, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; Bootstrap standard errors are presented in parentheses. * represents statistical significance at 5% level.

We also observe that exposure to income uncertainty varies systematically in the cross-section. As shown in Figure (2b) conditional dispersion follows a U-shape. Households at the top and bottom of the cross-sectional income distribution in $t-1$ face a larger dispersion of their income realisations in t compared to those in the middle of the distribution. Appendix Figures (11) and (12) confirm that the same pattern holds for other income measures and at different points in the life cycle. Taken together, these results suggest that income uncertainty varies systematically over the life cycle, within the cross-section and across skill groups.

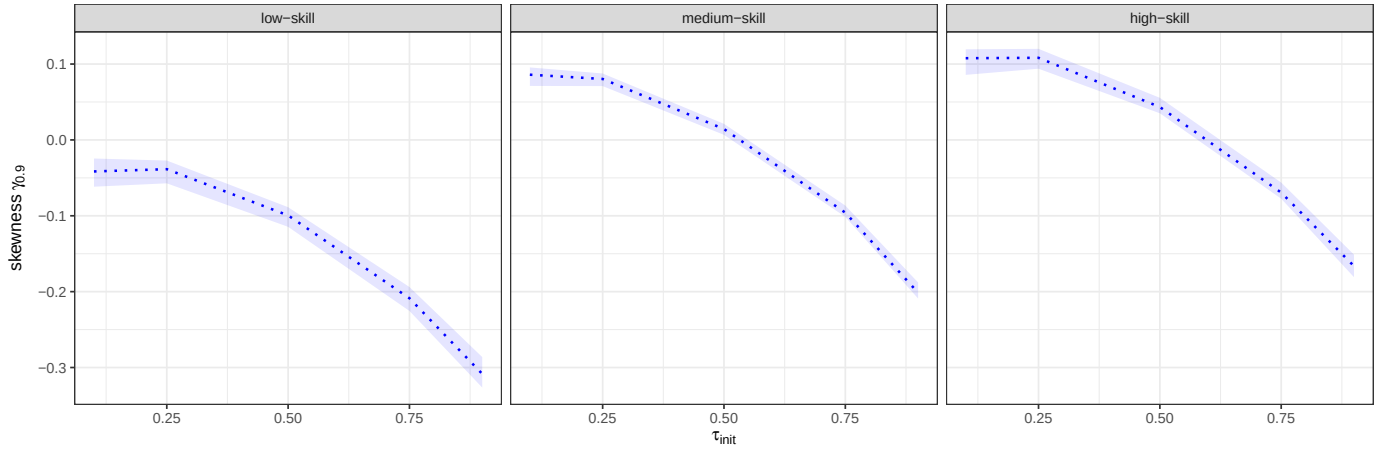
In Table (3) we report the cyclicality of conditional income uncertainty. Overall, the effects are quantitatively small. This is consistent with the empirical evidence reported in Guvenen, Ozkan, and Song (2014) and Busch, Domeij, Guvenen, and Madera (2016), who investigate the dispersion in income growth rates over the business cycle for the US, Germany and Sweden. However, we observe an interesting asymmetry in the cyclicality of conditional income dispersion. Households currently at the bottom of the cross-sectional income distribution experience an increase in the dispersion of their possible income realisations next period, while income realisations for those at the top becomes more compressed. This is in contrast to the median household, who faces an income uncertainty that remains largely unaffected by the expansion. For example, consider an increase in the growth rate of GDP by two standard deviations. For the medium-skilled, this implies that the log 90-10 market income differential decreases by around 0.0146 at the 90th percentile, it essentially remains unchanged for the median household (-0.004) and it increases for the household at the 10th percentile by 0.0188. To investigate the reason behind these asymmetric changes, we take a closer look at the movements in the tails of the conditional distribution. During

an expansion, our estimates of the conditional quantile functions reveal that the upper tail increases while the bottom tail shrinks. For the household at the 10th percentile, the upper tail increases relatively more than the bottom tail shrinks, which naturally leads to more dispersed income realisations in the following period. At the top of the distribution, however, it is the shrinkage of the bottom tail that outweighs the expansion of the upper tail, which therefore results in a compression of income realisations next period. Appendix Table (7) reveals that we find the same pattern using the unemployment rate as an alternative business cycle indicator.

We now shift attention to the asymmetry of the conditional distribution. Figure (3a) graphs the life cycle profile of the average skewness measure, defined in (9) and evaluated at $\tau = 0.9$.



(a) Average skewness over the life cycle



(b) Conditional skewness in family disposable income

Figure 3: Average and conditional skewness

Notes: This figure shows (a) the life cycle profile of average skewness, defined in (9) with $\tau = 0.90$, (b) conditional skewness in family disposable income, defined in (8) with $\tau = 0.90$ and evaluated at a value of $y_{i,t-1}$ that corresponds to theτ_{init} percentile of the distribution of $y_{i,t-1}$; 20 years of potential experience. The estimates are net of cohort and business cycle effects based on model (12). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (11), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δln(real GDP, det.), standardised	0.0133* (0.0015)	0.0219* (0.0011)	0.0157* (0.0014)	0.0161* (0.0014)	0.0277* (0.0010)	0.0130* (0.0013)	0.0151* (0.0014)	0.0287* (0.0010)	0.0141 (0.0012)

(a) low-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δln(real GDP, det.), standardised	0.0165* (0.0009)	0.0247* (0.0006)	0.0165* (0.0008)	0.0189* (0.0009)	0.0254* (0.0005)	0.0124* (0.0008)	0.0152* (0.0009)	0.0225* (0.0006)	0.0110* (0.0008)

(b) medium-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δln(real GDP, det.), standardised	0.0157* (0.0017)	0.0235* (0.0010)	0.0186* (0.0014)	0.0191* (0.0015)	0.0261* (0.0010)	0.0156* (0.0013)	0.0151* (0.0014)	0.0222* (0.0008)	0.0173* (0.0013)

(c) high-skilled

Table 4: Cyclicality of conditional skewness

Notes: This table presents the results of model (12). Cyclicality is captured by the coefficient on the change in detrended, real GDP of mainland Norway, normalised to have mean zero and unit standard deviation. The dependent variables are the cohort and time specific measures of conditional dispersion, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; Bootstrap standard errors are presented in parentheses. * represents statistical significance at 5% level.

First, note that there are only minor differences in the skewness profiles across the different measures of income. This is in stark contrast to the findings on average income dispersion, where we found a remarkable compression due to the tax- and transfer system and spouse's income. We observe that the tax- and transfer system leads to a slightly more left-skewed distribution early in the life cycle, while the opposite effect can be observed towards the end of the life cycle. When we add spouse's income, we find that this tends to further decrease skewness compared to individual disposable income. However, the effects are quantitatively small. Consider for example low-skilled households 10 years after completing education. Skewness in family disposable income is around -0.29 compared to -0.26 for market income. According to equation (10), this implies that the upper to lower tail ratio is around 36/64 for family disposable income compared to 35/65 for market income. More importantly, we find a more pronounced variation in skewness with potential experience. With 30 years of potential experience, the average upper to lower tail ratio in family disposable income is 47/53. Overall we find that average skewness roughly follows an inverted U-shape over the life cycle. Finally, a comparison across skill groups reveals that skewness risk decreases with educational attainment - leaving aside the comparably low skewness measure for the high skilled after 35 years of experience which most likely is a retirement effect.[12] With 20 years of experience, the upper to lower tail ratio is 43/57 for the low skilled, 49/51 for the medium-skilled and 50/50 for the high-skilled.

Consistent with the empirical evidence in Guvenen, Karahan, Ozkan, and Song (2016) and Arellano, Blundell, and Bonhomme (2016), we also find substantial variation in expo-

[12]Note, in particular, that high skilled with more than 35 years of experience are on average 60 years or older, while the low-skilled at this point in the life cycle are only in their early to mid 50's.

sure to skewness risk in the cross-section. Figure (3b) plots estimates for the conditional skewness (8) for households in the middle of the life cycle. Households who are at the top of the income distribution today are exposed to more skewness risk regarding their income realisations of tomorrow. Put differently, the likelihood of large downward movements is higher for those at the top compared to those at the bottom of today's cross-sectional distribution. Appendix Figures (13) and (14) show that roughly the same pattern can be observed for other income measures and at different points in the life cycle. Taken together, these results suggest that conditional skewness varies systematically over the life cycle, within the cross-section and across skill groups. In contrast to the findings on income dispersion, however, the tax and transfer system and the pooling of income at the household level does not appear to have a major impact on the exposure to skewness risk.

Finally, we shift attention to the cyclical properties of the conditional skewness measure reported in Table (4). Overall, we find that conditional skewness decreases during downturns, consistent with the empirical evidence in Guvenen, Ozkan, and Song (2014). Accordingly, in contractions negative income realisations are more likely than positive ones. Consider for example the low skilled with 20 years of experience. As shown in Figure (3b), the average conditional skewness in family disposable income for the median household is around -0.1, implying an upper to lower tail ratio of $45/55$. A drop in GDP growth by 2 standard deviations leads to a reduction in skewness by 0.0574 which corresponds to an upper-to-lower tail ratio of $42/58$. The magnitude of this effect is comparable to the estimates reported in Busch and Ludwig (2016) for Germany. Overall, cyclicality however does not appear to differ substantially across the different measures of income and across skill groups. We do, however, observe an asymmetry when we look at the effects in the cross-section. Conditional skewness appears to be more cyclical for households in the middle of the distribution compared to those at the top or bottom of the distribution, i.e. cyclicality appears to follow an inverted U-shape across the income distribution.

5 The Welfare Costs of Business Cycles

[Use this income process in a standard life cycle model of consumption and savings with aggregate shocks to investigate the distribution of the welfare costs of business cycles.]

6 Conclusion

[TBD]

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Appendix

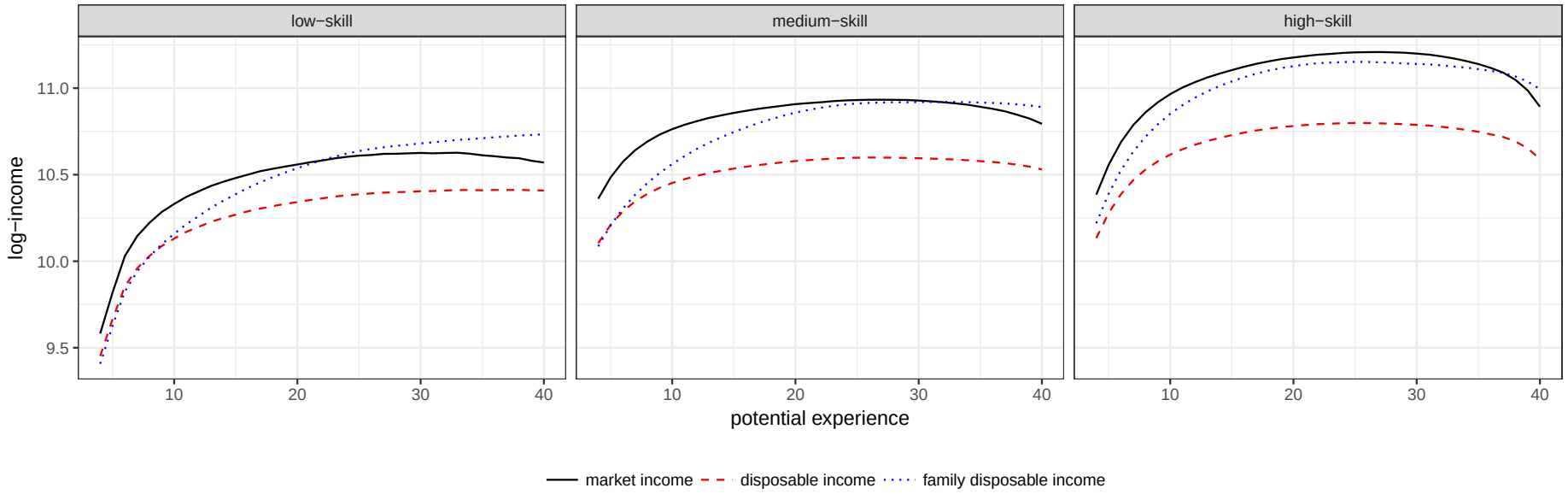


Figure 4: Age profiles in the log of income

Notes: This figure shows the age profiles in the log of income by educational levels. The age profiles are adjusted for education-specific calendar time effects. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

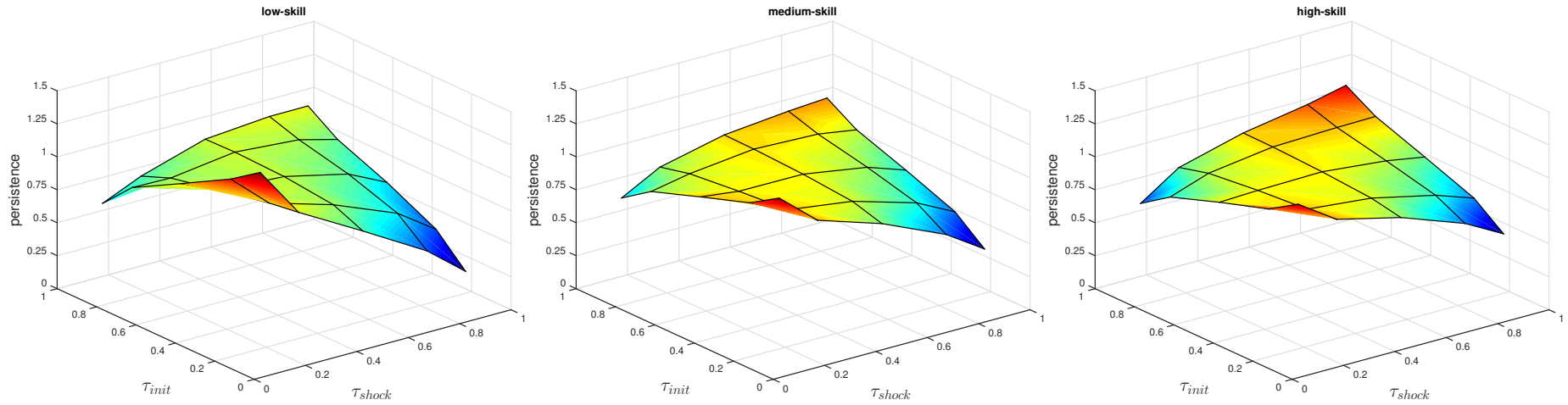


Figure 5: Persistence in family disposable income

Notes: This figure shows the average persistence in family disposable income for households with 20 years of experience. Persistence is defined in (5) as the derivative of the conditional quantile function of y_{it} with respect to $y_{i,t-1}$. For each cohort and time period we evaluate the derivative at the rank of the income shock (τ_{shock}) and at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the time and cohort specific distribution of $y_{i,t-1}$. Cohort and business cycle effects are taken out based on model (12). Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

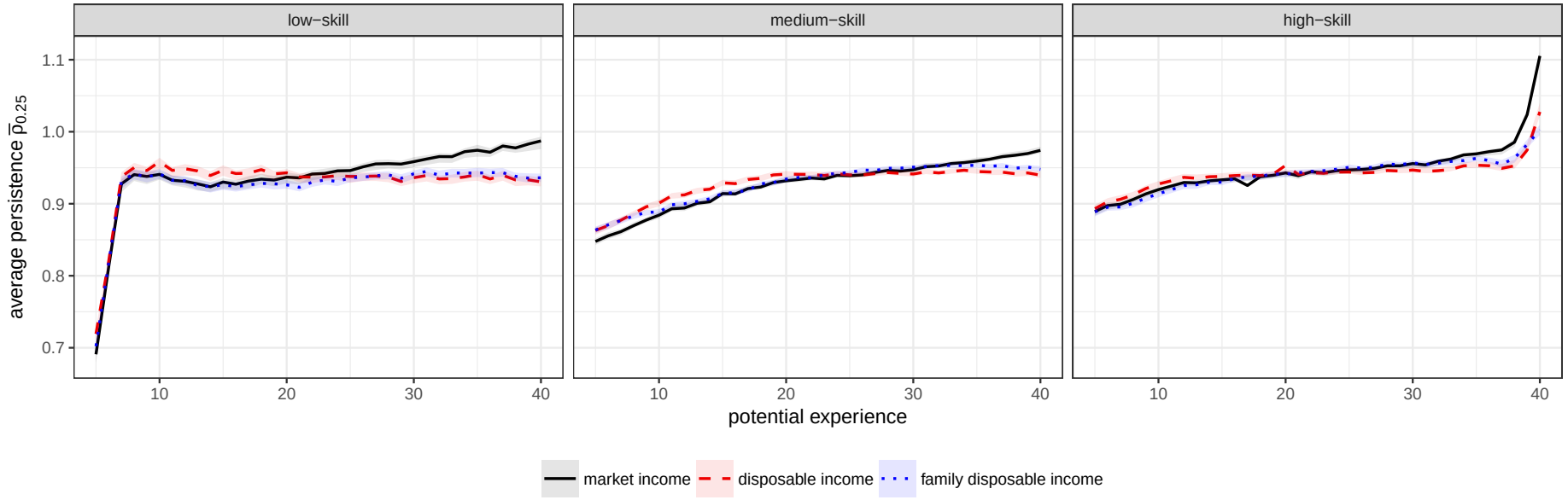


Figure 6: Average persistence over the life cycle: $\bar{\rho}(0.25)$

Notes: This figure shows the average persistence of a shock of rank 0.25, given by $\bar{\rho}_t(0.25) = \mathbb{E}\frac{\partial Q_t(y_{i,t-1},0.25)}{\partial y_{i,t-1}}$. Cohort and business cycle effects are taken out based on model (12). Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

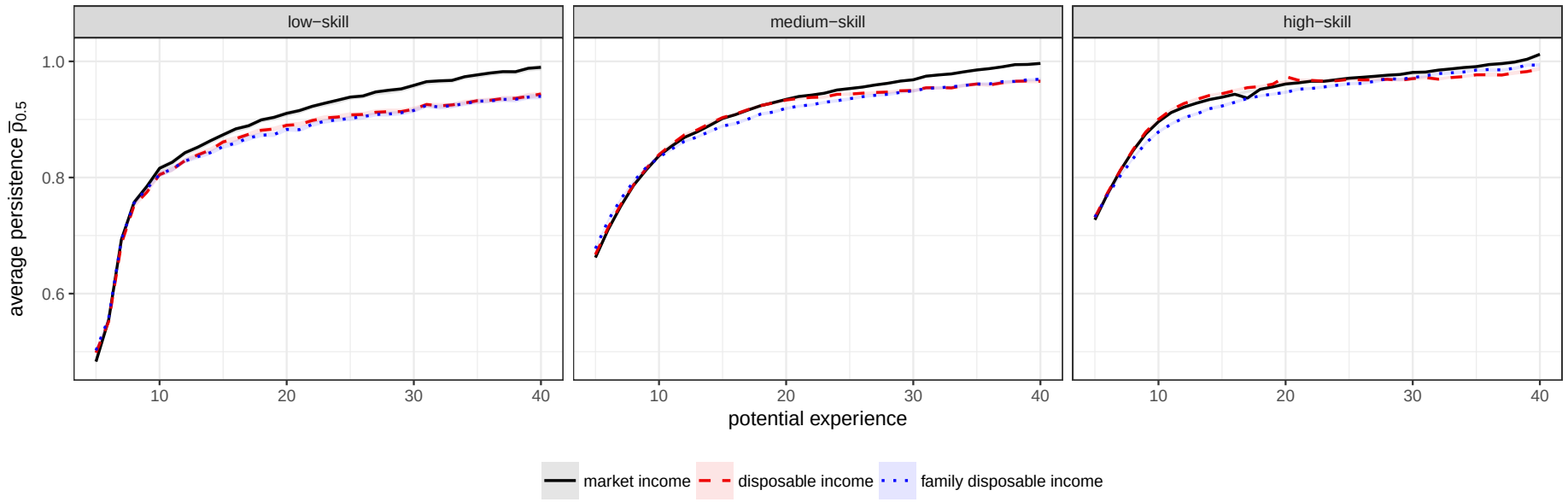


Figure 7: Average persistence over the life cycle

Notes: This figure shows the average persistence of a shock of rank 0.5, given by $\bar{\rho}_t(0.5) = \mathbb{E}\frac{\partial Q_t(y_{i,t-1},0.5)}{\partial y_{i,t-1}}$. Cohort and business cycle effects are taken out based on model (12). Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

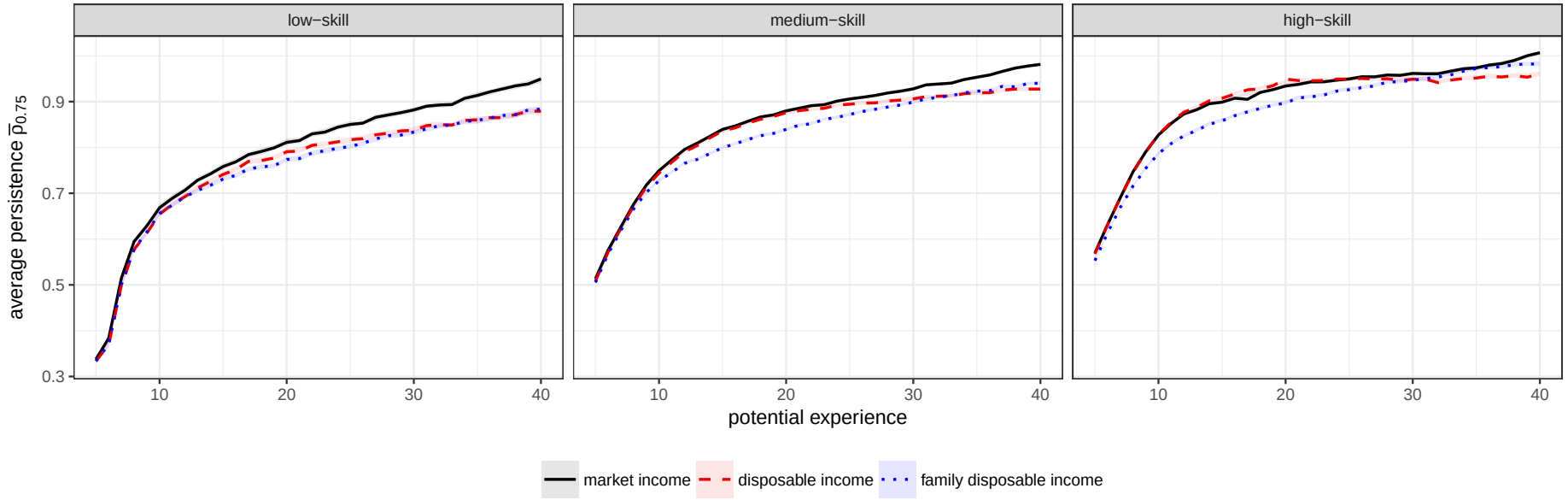


Figure 8: Average persistence over the life cycle

Notes: This figure shows the average persistence of a shock of rank 0.5, given by $\bar{\rho}_t(0.75) = \mathbb{E}\frac{\partial Q_t(y_{i,t-1},0.75)}{\partial y_{i,t-1}}$. Cohort and business cycle effects are taken out based on model (12). Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

	market income		disposable income		family disposable income	
unemp. rate, de-meaned	-0.046^{***}		-0.041^{***}		-0.034^{***}	
	(0.000)		(0.000)		(0.000)	
$\mathbb{1}\{\text{exp.}=5\}\times$unemp. rate		-0.104^{***}		-0.099^{***}		-0.101^{***}
		(0.002)		(0.002)		(0.002)
$\mathbb{1}\{\text{exp.}=10\}\times$unemp. rate		-0.052^{***}		-0.043^{***}		-0.036^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=20\}\times$unemp. rate		-0.044^{***}		-0.041^{***}		-0.029^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=30\}\times$unemp. rate		-0.023^{***}		-0.023^{***}		-0.017^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=40\}\times$unemp. rate		-0.034^{***}		-0.031^{***}		-0.028^{***}
		(0.002)		(0.001)		(0.001)
R^2	0.16	0.16	0.26	0.27	0.49	0.50
Num. Obs.	5,377,227	5,377,227	5,377,227	5,377,227	5,377,227	5,377,227

(a) low-skilled

	market income		disposable income		family disposable income	
unemp. rate, de-meaned	-0.036^{***}		-0.026^{***}		-0.019^{***}	
	(0.000)		(0.000)		(0.000)	
$\mathbb{1}\{\text{exp.}=5\}\times$unemp. rate		-0.068^{***}		-0.058^{***}		-0.057^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=10\}\times$unemp. rate		-0.039^{***}		-0.028^{***}		-0.016^{***}
		(0.001)		(0.000)		(0.000)
$\mathbb{1}\{\text{exp.}=20\}\times$unemp. rate		-0.035^{***}		-0.024^{***}		-0.016^{***}
		(0.001)		(0.000)		(0.000)
$\mathbb{1}\{\text{exp.}=30\}\times$unemp. rate		-0.022^{***}		-0.014^{***}		-0.010^{***}
		(0.001)		(0.000)		(0.000)
$\mathbb{1}\{\text{exp.}=40\}\times$unemp. rate		-0.039^{***}		-0.025^{***}		-0.025^{***}
		(0.001)		(0.001)		(0.001)
R^2	0.17	0.17	0.28	0.28	0.54	0.54
Num. Obs.	14,106,136	14,106,136	14,106,136	14,106,136	14,106,136	14,106,136

(b) medium-skilled

	market income		disposable income		family disposable income	
unemp. rate, de-meaned	-0.034^{***}		-0.015^{***}		-0.010^{***}	
	(0.000)		(0.000)		(0.000)	
$\mathbb{1}\{\text{exp.}=5\}\times$unemp. rate		-0.046^{***}		-0.037^{***}		-0.034^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=10\}\times$unemp. rate		-0.035^{***}		-0.019^{***}		-0.010^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=20\}\times$unemp. rate		-0.034^{***}		-0.012^{***}		-0.006^{***}
		(0.001)		(0.001)		(0.000)
$\mathbb{1}\{\text{exp.}=30\}\times$unemp. rate		-0.026^{***}		-0.006^{***}		-0.003^{***}
		(0.001)		(0.001)		(0.001)
$\mathbb{1}\{\text{exp.}=40\}\times$unemp. rate		-0.012^{***}		-0.002		-0.002
		(0.003)		(0.002)		(0.002)
R^2	0.22	0.22	0.30	0.30	0.55	0.55
Num. Obs.	7,789,349	7,789,349	7,789,349	7,789,349	7,789,349	7,789,349

(c) high-skilled

Table 5: Aggregate cyclical income risk: Unemployment rate

Notes: This table present coefficients of pooled OLS regressions. The results from specifications (2) and (3) are presented in column (1) and (2) respectively. The business cycle indicator is the demeaned unemployment rate. Other controls include potential experience fixed effects, cohort fixed effects, region fixed effects and marital status and dummies for the number of children in the household. Standard errors are presented in parentheses, and are clustered at the individual-level. ***, **, and *, represent statistical significance at 0.1%, 1%, and 5% levels, respectively.

	market income		disposable income		family disposable income	
ln(real GDP, det.)	1.570***		1.228***		1.155***	
	(0.018)		(0.014)		(0.013)	
𝟙{exp.=5}×ln(real GDP, det.)		3.854***		3.141***		3.153***
		(0.143)		(0.118)		(0.118)
𝟙{exp.=10}×ln(real GDP, det.)		2.005***		1.419***		1.289***
		(0.102)		(0.081)		(0.079)
𝟙{exp.=20}×ln(real GDP, det.)		1.335***		1.011***		1.024***
		(0.101)		(0.077)		(0.072)
𝟙{exp.=30}×ln(real GDP, det.)		1.133***		0.844***		0.757***
		(0.089)		(0.062)		(0.055)
𝟙{exp.=40}×ln(real GDP, det.)		1.208***		1.158***		1.014***
		(0.184)		(0.098)		(0.087)
R^2	0.58	0.58	0.56	0.57	0.71	0.71
Household FE?	yes	yes	yes	yes	yes	yes
Num. Obs.	5,377,227	5,377,227	5,377,227	5,377,227	5,377,227	5,377,227

(a) low-skilled

	market income		disposable income		family disposable income	
ln(real GDP, det.)	1.179***		0.919***		0.839***	
	(0.009)		(0.007)		(0.006)	
𝟙{exp.=5}×ln(real GDP, det.)		2.421***		1.821***		1.794***
		(0.073)		(0.058)		(0.057)
𝟙{exp.=10}×ln(real GDP, det.)		1.282***		0.921***		0.837***
		(0.053)		(0.039)		(0.038)
𝟙{exp.=20}×ln(real GDP, det.)		1.285***		0.921***		0.818***
		(0.045)		(0.033)		(0.030)
𝟙{exp.=30}×ln(real GDP, det.)		0.783***		0.662***		0.602***
		(0.053)		(0.038)		(0.033)
𝟙{exp.=40}×ln(real GDP, det.)		0.914***		0.865***		0.776***
		(0.099)		(0.060)		(0.049)
R^2	0.55	0.55	0.60	0.60	0.75	0.75
Household FE?	yes	yes	yes	yes	yes	yes
Num. Obs.	14,106,136	14,106,136	14,106,136	14,106,136	14,106,136	14,106,136

(b) medium-skilled

	market income		disposable income		family disposable income	
ln(real GDP, det.)	0.832***		0.556***		0.516***	
	(0.012)		(0.010)		(0.009)	
𝟙{exp.=5}×ln(real GDP, det.)		1.984***		1.506***		1.383***
		(0.096)		(0.079)		(0.076)
𝟙{exp.=10}×ln(real GDP, det.)		0.881***		0.551***		0.451***
		(0.059)		(0.047)		(0.044)
𝟙{exp.=20}×ln(real GDP, det.)		0.863***		0.489***		0.442***
		(0.057)		(0.047)		(0.041)
𝟙{exp.=30}×ln(real GDP, det.)		0.415***		0.346***		0.295***
		(0.069)		(0.055)		(0.047)
𝟙{exp.=40}×ln(real GDP, det.)		-0.292		−0.408*		−0.091
		(0.223)		(0.180)		(0.132)
R^2	0.61	0.61	0.64	0.64	0.77	0.77
Household FE?	yes	yes	yes	yes	yes	yes
Num. Obs.	7,789,349	7,789,349	7,789,349	7,789,349	7,789,349	7,789,349

(c) high-skilled

Table 6: Aggregate cyclical income risk: Household fixed effects

Notes: This table present coefficients of household fixed effects regressions. The business cycle indicator is the HP-filtered natural logarithm of real GDP of mainland Norway. Other controls include potential experience fixed effects, region fixed effects, marital status and dummies for the number of children in the household. Standard errors are presented in parentheses, and are clustered at the individual-level. ***, **, and *, represent statistical significance at 0.1%, 1%, and 5% levels, respectively.

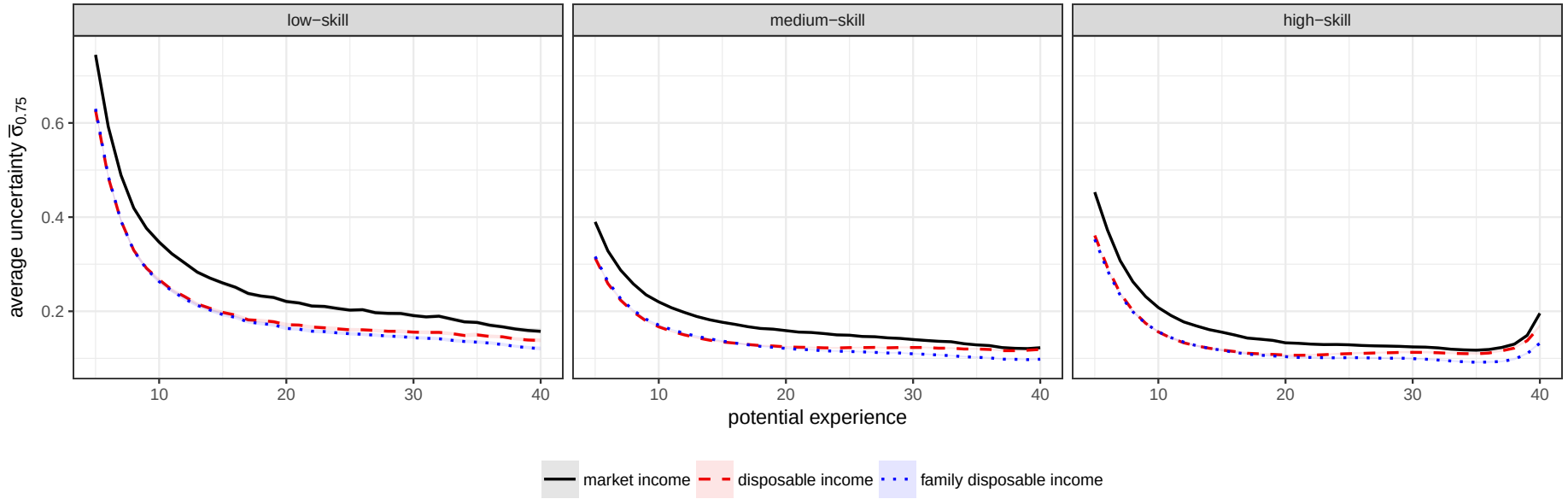


Figure 9: Average dispersion over the life cycle

Notes: This figure shows the life cycle profile of the average dispersion defined in (7) with $\tau = 0.75$. The life cycle profiles are based on model (*12*). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (*11*), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

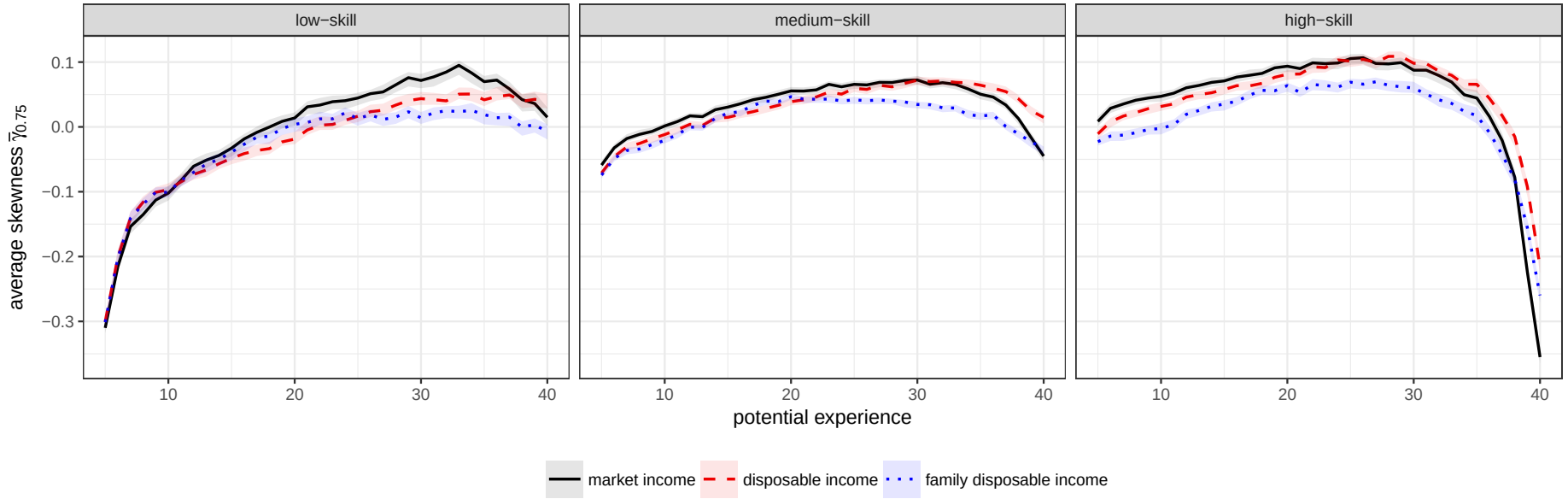
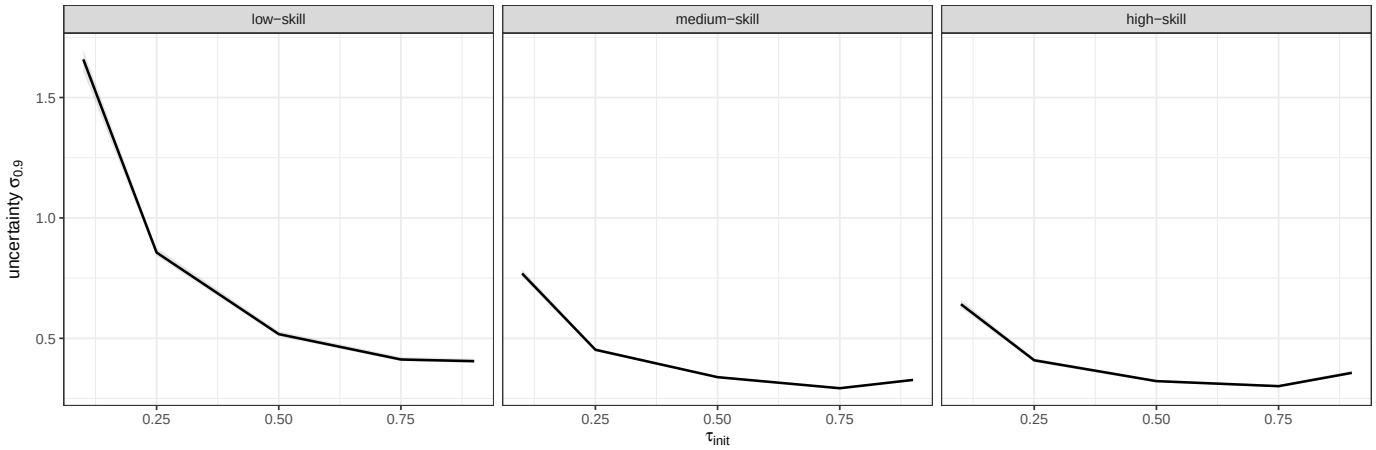
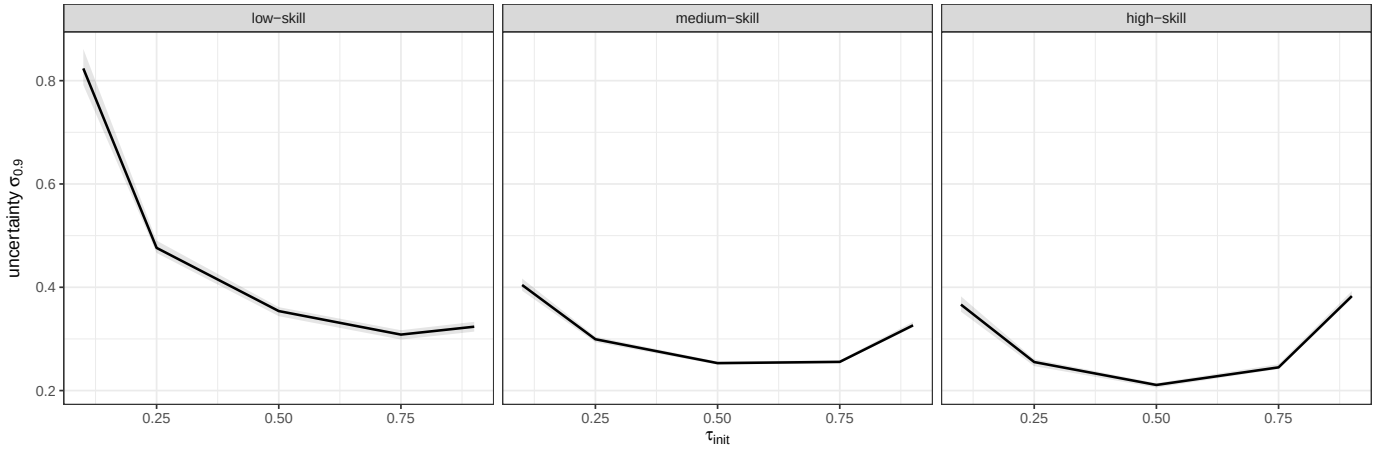


Figure 10: Average skewness over the life cycle

Notes: This figure shows the life cycle profile of the average Bowley skewness defined in (9) with $\tau = 0.75$. The life cycle profiles are based on model (*12*). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (*11*), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.



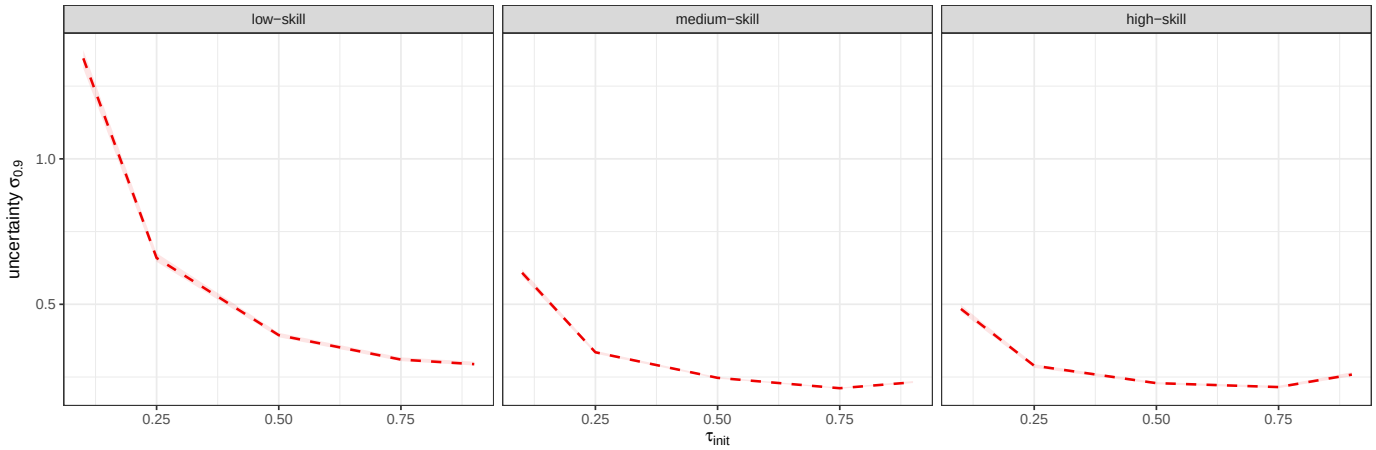
(a) 10 years of potential experience



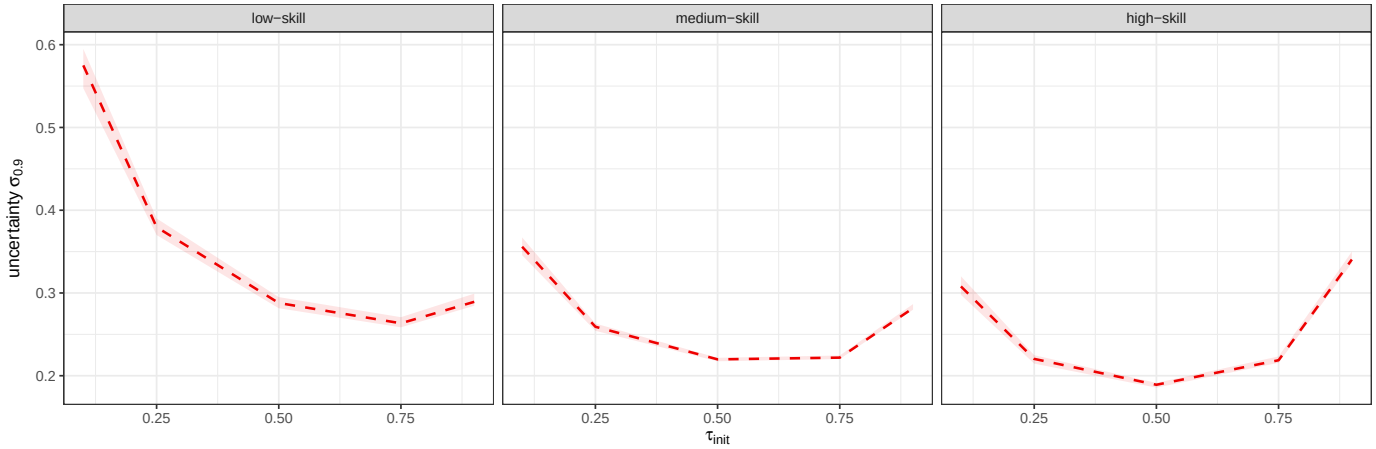
(b) 30 years of potential experience

Figure 11: Conditional dispersion in market income

Notes: This figure shows the conditional dispersion in market income, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; 10 and 30 years of potential experience. The estimates are net of cohort and business cyle effects based on model (12). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (11), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.



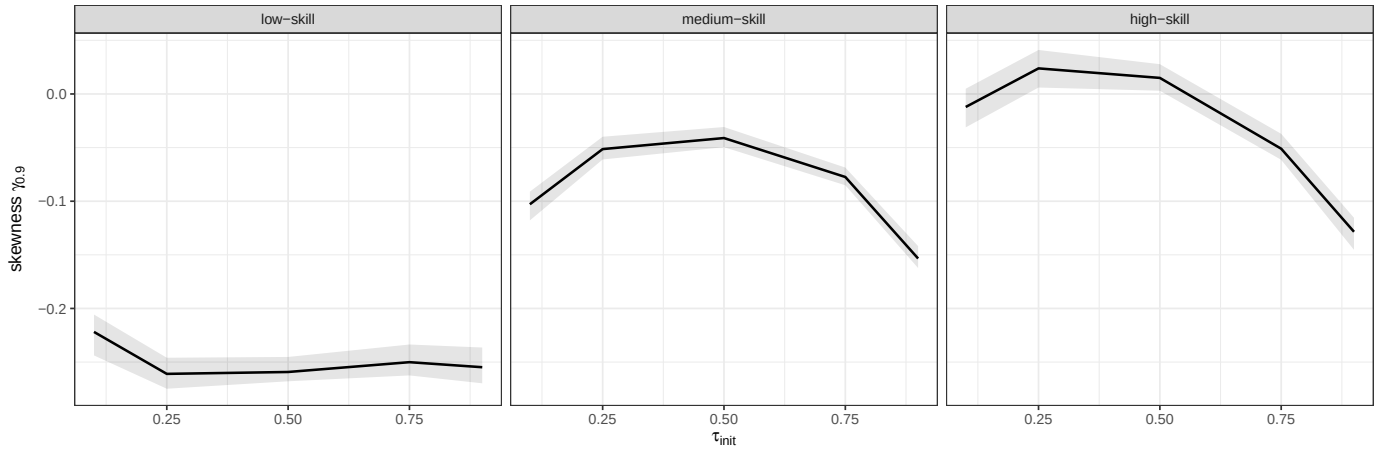
(a) 10 years of potential experience



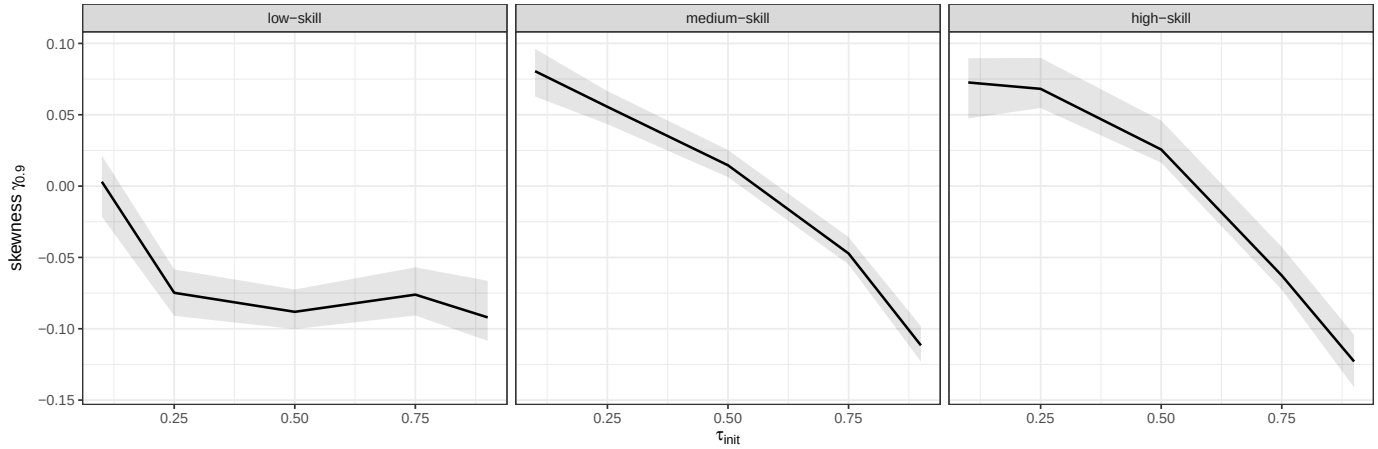
(b) 30 years of potential experience

Figure 12: Conditional dispersion in disposable income

Notes: This figure shows the conditional dispersion in disposable income, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; 10 and 30 years of potential experience. The estimates are net of cohort and business cycle effects based on model (12). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (11), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.



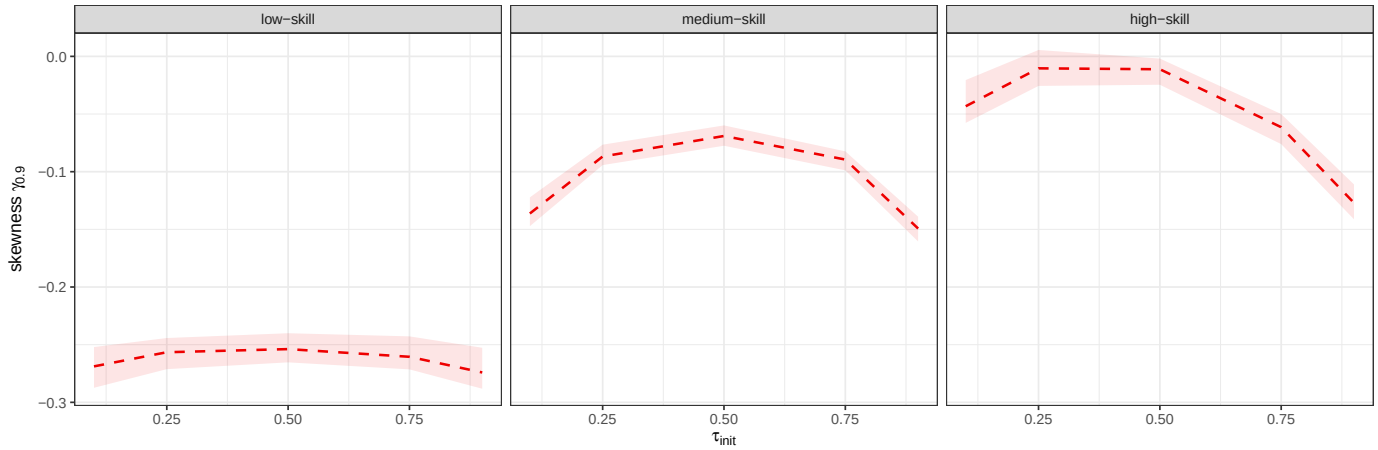
(a) 10 years of potential experience



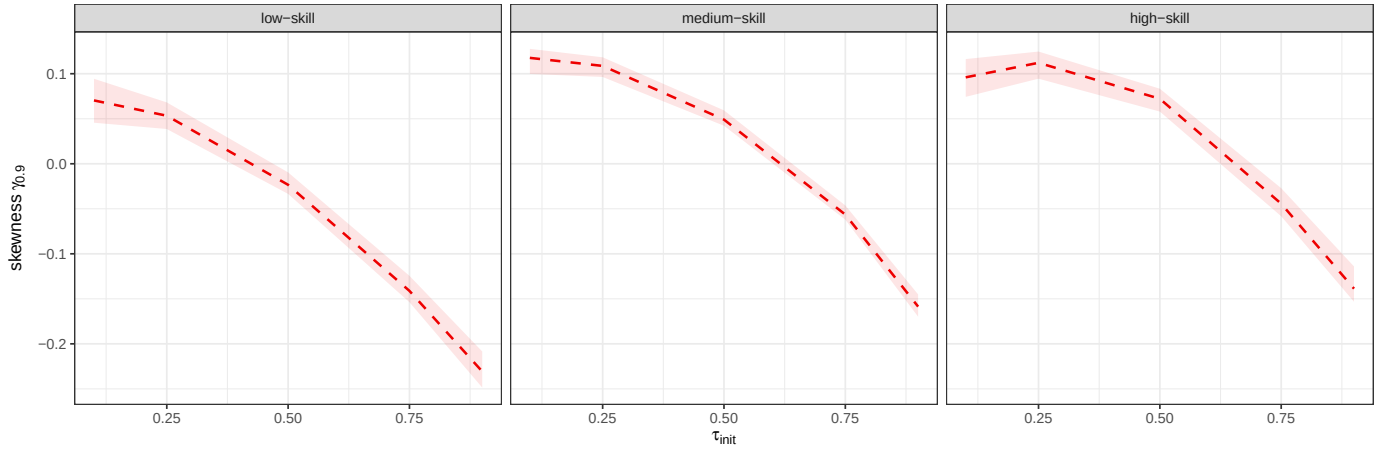
(b) 30 years of potential experience

Figure 13: Conditional skewness in market income

Notes: This figure shows the conditional skewness in market income, defined in (8) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; 10 and 30 years of potential experience. The estimates are net of cohort and business cycle effects based on model (12). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (11), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.



(a) 10 years of potential experience



(b) 30 years of potential experience

Figure 14: Conditional skewness in disposable income

Notes: This figure shows the conditional skewness in disposable income, defined in (8) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; 10 and 30 years of potential experience. The estimates are net of cohort and business Kyle effects based on model (12). Shaded areas represent 95% point-wise confidence intervals based on non-parametric bootstrap of the quantile auto-regressions (11), clustered at the household level, with 100 replications. Low skilled is defined as not having completed high school, medium skilled includes individuals with a high school degree, and high skilled consists of individuals who have attended college. Potential labour market experience is defined as age minus years of education minus 6.

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δunemp. rate	-0.0258^*	0.0020^*	0.0105^*	-0.0227^*	0.0011^*	0.0071^*	-0.0233^*	0.0004	0.0071^*
standardised	(0.0020)	(0.0006)	(0.0006)	(0.0014)	(0.0004)	(0.0005)	(0.0013)	(0.0005)	(0.0005)

(a) low-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δunemp. rate	-0.0035^*	0.0023^*	0.0037^*	-0.0050^*	0.0018	0.0017	-0.0078	0.0008	0.0024
standardised	(0.0007)	(0.0002)	(0.0003)	(0.0006)	(0.0001)	(0.0002)	(0.0005)	(0.0001)	(0.0002)

(b) medium-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δunemp. rate	-0.0049^*	-0.0007^*	-0.0021^*	-0.0060^*	-0.0002^*	-0.0010^*	-0.0081^*	-0.0009^*	-0.0002
standardised	(0.0005)	(0.0001)	(0.0002)	(0.0008)	(0.0002)	(0.0004)	(0.0007)	(0.0002)	(0.0004)

(c) high-skilled

Table 7: Cyclicality of conditional dispersion

Notes: This table presents the results of model (12). Cyclicality is captured by the coefficient on the change in the unemployment rate, normalised to have mean zero and unit standard deviation. The dependent variables are the cohort and time specific measures of conditional dispersion, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; Bootstrap standard errors are presented in parentheses. * represents statistical significance at 5% level.

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δunemp. rate	-0.0213^*	-0.0387^*	-0.0346^*	-0.0132^*	-0.0416^*	-0.0282^*	-0.0146^*	-0.0393^*	-0.0278^*
standardised	(0.0014)	(0.0010)	(0.0014)	(0.0013)	(0.0009)	(0.0014)	(0.0013)	(0.0010)	(0.0012)

(a) low-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δunemp. rate	-0.0312^*	-0.0441^*	-0.0251^*	-0.0254^*	-0.0397^*	-0.0184^*	-0.0186^*	-0.0322^*	-0.0172^*
standardised	(0.0010)	(0.0007)	(0.0009)	(0.0009)	(0.0006)	(0.0009)	(0.0009)	(0.0006)	(0.0009)

(b) medium-skilled

	market income			disposable income			family disposable income		
τ_{init}	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
Δunemp. rate	-0.0217^*	-0.0284^*	-0.0164^*	-0.0176^*	-0.0256^*	-0.0141^*	-0.0131^*	-0.0186^*	-0.0138^*
standardised	(0.0018)	(0.0010)	(0.0014)	(0.0018)	(0.0011)	(0.0013)	(0.0015)	(0.0009)	(0.0014)

(c) high-skilled

Table 8: Cyclicality of conditional skewness

Notes: This table presents the results of model (12). Cyclicality is captured by the coefficient on the change in HP-filtered log real GDP of mainland Norway, normalised to have mean zero and unit standard deviation. The dependent variables are the cohort and time specific measures of conditional skewness, defined in (6) with $\tau = 0.9$ and evaluated at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$; Bootstrap standard errors are presented in parentheses. * represents statistical significance at 5% level.