König, Johannes; Longmuir, Maximilian

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DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
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Wage Risk and Portfolio Choice: The Role of Correlated Returns*

Johannes König Maximilian Longmuir
DIW Berlin† Freie Universität Berlin‡

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Abstract

From standard portfolio-choice theory it is well-understood that background risk, overwhelmingly due to wage risk, is one of the central determinants of individuals' portfolio composition: higher background risk reduces risky investments. However, if background risk is negatively correlated with financial market risk, higher background risk implies more risky investment. We quantify the influence of wage risk on German investors' financial portfolio shares and find that an increase of the residual variance of wages by one standard deviation implies a reduction of the financial portfolio share by 3 percentage points. We do not find that the correlation of wage risk with financial market risk has a significant impact on portfolio choice and provide evidence that this may be due to a lack of salience.

Keywords: Background Risk, Portfolio Choice , Household Portfolios, Investment Behavior
JEL Classifications: D12, D14, D31,

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†DIW Berlin/SOEP, Mohrenstr. 58, 10117 Berlin, Germany (e-mail: jkoenig@diw.de).

‡Department of Economics, Freie Universität Berlin, Boltzmannstr. 20, 14195 Berlin, Germany (e-mail: maximilian.wenzel@fu-berlin.de).

1 Introduction

Unpredictable and uninsurable shocks to labor income affect households' portfolio choice. In standard portfolio choice models, the optimal risky portfolio share reduces when households face higher degrees of labor income risk (Heaton and Lucas, 2000; Cocco et al., 2005; Guiso and Paiella, 2008; Cardak and Wilkins, 2009; Betermier et al., 2012; Fagereng et al., 2018). These standard models typically assume that the correlation between labor income risk and asset return risk is (close to) zero (Guiso and Sodini, 2013). This assumption is not innocuous. For example, when risky asset returns are negatively correlated with labor income risk, investing in risky assets actually hedges labor income risk. Thus, it is crucial for individuals to consider the correlation when minimizing overall risk exposure. Ultimately, whether the theory holds, is an empirical question. Hence, in this paper, we quantify the influence of wage risk and its correlation with financial market returns on German investors' financial portfolio shares.

Labor income risk is one of the prime components of background risk (Guiso and Sodini, 2013; Gomes et al., 2021). Investigating background risk is important for our understanding of individuals' investment behavior. Previous research has concluded that individuals do not follow standard portfolio choice theory and invest too little of their portfolio in risky assets (Calvet et al., 2007). Background risk serves as one of the explanations to reconcile this discrepancy between empirics and theory. From a welfare economics perspective, background risk is beyond the control of the individual (Eeckhoudt et al., 1996). Thus, alleviating individuals' exposure to background risk, either by offering insurance on the labor market, or improving individuals' portfolio choice, may also induce welfare gains. Finally, since labor income risk impacts individuals disparately, it may not only lead to income inequality, but through its influence on portfolio choice, drive wealth inequality (Benhabib et al., 2017).

Both the precise definition and the quantification of background risk are demanding. In most applications authors restrict their view to yearly labor income risk. Even when we restrict our attention to labor income risk, two important concerns are in the way of identifying an effect on portfolio choice: an omitted variable bias and measurement error. The omitted variable bias arises, because risk preferences are heterogeneous in the population and affect not only portfolio choice but also various decisions in the labor market, for example, job choice or educational attainment (Brown et al., 2006; Bonin et al., 2007; Dohmen et al., 2011). The measurement error bias emerges, since only a part of the risk that the econometrician measures is due to exogenous shocks that the individual cannot control. To address the omitted variable bias, the literature has relied on specifications with fixed effects. To address measurement error bias, instrumental variables (IV) have been used (Fagereng et al., 2018).

We follow the literature and address these problems by estimating a fixed effects IV regression. Concerning the measurement error bias, we use hourly wages and not labor income to quantify risk. Idiosyncratic wage fluctuations are generally not attributable to individual choice compared to variations in labor income (Blundell et al., 2016). Hence, we tackle part of the measurement error problem through the selection of the focal variable.

Wages are also comparable to asset returns, since they represent the payoff to human capital investment. Therefore, we prefer wages, instead of labor income, when we calculate the correlation with financial market returns.

To thoroughly treat the measurement error problem, in line with literature (Betermier et al., 2012; Fagereng et al., 2018), we construct a group-IV based on occupational, time, and fine-grained regional information (Blundell et al., 1998; Blau and Kahn, 2006; Burns and Ziliak, 2017). We interact dummies of the occupational, time, and regional information to construct well-differentiated groups. This IV captures variation in local labor market conditions. For example, take the case of an automobile plant opening in a specific region. Due to the plant opening, demand for certain occupations (e.g. mechanics), will rise, changing their wages. These types of shocks are beyond the control of the individual and thus identify background risk. In this sense, the variation we use for our IV is very similar to the IV established in Fagereng et al. (2018), which relies on firm-specific productivity shocks and links them to individuals working in these firms. Their IV also behaves like a group IV, since all workers in a certain firm experience the productivity shock. Our IV is bound to react to a broader array of shocks, for example, changes in bargaining power, firm closures and openings, or differences in development trends of regional infrastructure, however, the general idea of the identification strategy is the same.

First, we find that the coefficient of the influence of wage risk on the financial portfolio share falls from about -0.03 in the fixed effects specification to about -0.09 in the IV fixed effects specification. Classical measurement error attenuates coefficient estimates toward zero, which the IV estimator alleviates. This effect is robust to several changes in the control variable specification, an alternative definition of the risk measure, and restrictions on the working sample. Moreover, we systematically exclude groups from our group IV to ensure that single groups do not drive our results.

Second, the coefficient of the correlation of wage risk with financial asset returns is never statistically significant in our regressions of the financial share. This is in contradiction with standard portfolio choice models, which would predict that higher correlation with financial markets leads to a smaller share invested. While the correlation is zero on average, as we will show, its variance is large, suggesting the possibility to find a significant coefficient.[1] We suspect that we cannot find an effect, because of a lack of salience with respect to the correlation. As a test of this hypothesis, we regress a subjective measure of economic worries on the wage risk and the correlation both in OLS and IV specifications. As in the portfolio choice regressions, wage risk significantly increases economic worries, while the correlation between wage risk and asset returns is not significant.

[1]Most of the evidence regarding the correlation of labor income and financial market returns rests on aggregate and not individual level correlations (Guiso and Sodini, 2013; Gomes et al., 2021). Davis and Willen (2014) find large and significant correlations of residual occupation-specific wages with a portfolio sorted on firm size. Bottazzi et al. (1996) use a VAR model to derive the correlation between human capital and financial return innovation and finding them to be negative on average (about -0.4). The correlation between aggregate labor income and stock market returns is high, but aggregate fluctuation make up only 10 percent of total labor income variance Campbell et al. (2009); Gomes et al. (2021). However, the correlation with variation of other components of labor income, e.g. industry and individual level components, is less well-understood.

To facilitate the analysis we rely on the German Social Economic Panel (SOEP), which contains long-running panel data on hourly wages and wealth portfolios. Further, SOEP offers the labor market characteristics of individuals and the fine-grained regional information that we need to construct the IV. Additionally, we use financial market data from the Thomson Reuters Eikon database to construct the correlation.

Our paper makes three contributions to the literature: first, we quantify the influence of hourly wage risk on portfolio choice and find that the size of its effect is of comparable magnitude to those found in the existing literature. Second, using a new IV-strategy we show the considerable influence of wage risk on portfolio choice in an economically important country with considerable heterogeneity in both asset holdings and wage risk, i.e. Germany. Third, to the best of our knowledge, we are the first to empirically quantify the influence of the correlation between financial market returns and wage risk on portfolio choice and we give an explanation as to why this influence is neither statistically, nor economically, significant.

Background risk, especially income risk and its effect on portfolio holdings, has been studied extensively in the literature. Heaton and Lucas (1999, 2000) show with a life cycle model of consumption and portfolio choice with non-tradable labor income, that households with higher background risk hold less financial assets. Cocco et al. (2005) include various correlations between income variance and asset returns in their calibrated decision-theoretic models, showing that even small, positive correlations reduce the risky portfolio share. Buraschi et al. (2010) provide a multivariate model framework to show that risk correlations affect the optimal portfolio choice.

Several studies provide empirical evidence for the importance of background risk. Guiso and Paiella (2008), using Italian survey data, show that background risk and borrowing restrictions shape consumers risk aversion and, therefore, background risk decreases the willingness to take risk on financial markets. Cardak and Wilkins (2009) find a significant correlation between income risk and risky portfolio holdings in Australia, while Betermier et al. (2012) find a causal effect between the increase of income risk and the decrease of risky portfolio holdings in Sweden. Recently, Fagereng et al. (2017) include uninsurable labor income as a fundamental component to estimate portfolio choice over the life cycle in Norway. Fagereng et al. (2018) link individual workers to their firms to use the variability in the profitability of the firm as a measure of labor market risk.

Our findings, beyond quantifying the influence of wage risk on portfolio choice and testing the influence of the correlation with financial market returns, have important implications in the areas of household finance and welfare economics. Our study implies that individuals make considerable investment mistakes by disregarding the correlation of their asset portfolio returns and wage risk. Individuals could improve their investment strategy by receiving information on this correlation structure and thus decrease their overall risk exposure, and increase their welfare.

The rest of the paper is organized as follows. Section 2 presents a simple model of portfolio choice with correlated labor income and financial market returns. Section 3 presents our two datasources: the Socio-Economic Panel and the Thomson Reuters Eikon

database. Section 4 shows how we construct our variables for analysis and the specifications we implement. Section 5 presents our main results, section 6 details our robustness checks, and section 7 concludes.

2 A Two-Period Model of Portfolio-Choice

The Model To start, we provide relevant theoretical insight into labor market risk, especially the variance of labor income and its correlation with asset returns. Then we show how both risks affect portfolio choice, i.e. the optimal risky portfolio share. We show simulations from a two-period model, where an individual receives some wealth and risk-free income in the first period and risky labor income as well as asset returns in the second period. The individual chooses consumption, and hence saving, in the first period as well as the share invested in a risky asset. Then, we introduce correlation between the risky asset returns and risky labor income. The model does not feature labor supply, so wages and income are equivalent.

The formulation and parametrization of the model follows Cocco et al. (2005).[2] Apart from not featuring a longer time-horizon, we also disregard the bequest motive and labor supply. This reduction in complexity is acceptable, since the model is only intended to illustrate individuals' reactions to changes in risk and the correlation of risk factors, which are qualitatively unaffected by this reduction in complexity.[3]

An individual's utility exhibits constant relative risk aversion and thus the individual maximizes:

$$\max_{c_1,c_2,\omega} E\left[\frac{c_1^{1-\sigma}}{1-\sigma} + \beta\frac{c_2^{1-\sigma}}{1-\sigma}\right], \tag{1}$$

where c_1 and c_2 denote first and second period consumption respectively and the parameter σ determines relative risk aversion. The maximization is subject to the inter-temporal budget constraint given by

$$c_2 = w_2 + R\omega(w_1 - c_1 + a_1) + (1+r)(1-\omega)(w_1 - c_1 + a_1), \tag{2}$$

where w_1 and w_2 is labor income, a_1 is the stock of assets in the first period, $(1+r)$ is the non-risky return on the safe asset, R is the risky return, and ω is the share invested in the risky asset (risky share). Unlike w_1, w_2 is risky and, together with R, they are log-normally distributed with the underlying normal distribution:

$$\{\log w_2, \log R\} \sim N\left(\begin{pmatrix} \log w_1 - \frac{\sigma_w^2}{2} \\ \log(1+r+\tilde{e}) - \frac{\sigma_R^2}{2} \end{pmatrix}, \begin{pmatrix} \sigma_w^2 & \rho\sigma_w\sigma_R \\ \rho\sigma_w\sigma_R & \sigma_R^2 \end{pmatrix}\right), \tag{3}$$

where the mean of w_2 is w_1 and the mean of R is given by $1+r+\tilde{e}$, i.e. the safe return plus an expected excess return. The standard deviation of the log of w_2 and the log of

[2] See page 501, Table 4.

[3] For example, one can think of this model as looking at a decision between two periods in a model with more than two periods. Further, regarding labor supply, as long as individuals still have incentive to work, they will still partially be subject to labor income risk.

R are σ_w and σ_R, respectively, and the correlation $\log w_2$ and $\log R$ is ρ. In the following exercises, we will vary σ_w, σ_R, and ρ to illustrate their influence on the choice of ω. The baseline calibration of the model is given in Table 1.

Table 1. Baseline Calibration

Description	Variable	Value
CRRA parameter	σ	10
first period assets	a_1	25000
first period labor income	w_1	25000
s.d. of risky income	σ_w	0.15
discount factor	β	0.96
non-risky return	r	0.02
expected excess return	$\tilde{e}$	0.04
s.d. risky asset	σ_R	0.157
correlation between $\log w_2$ and $\log R$	ρ	0.0

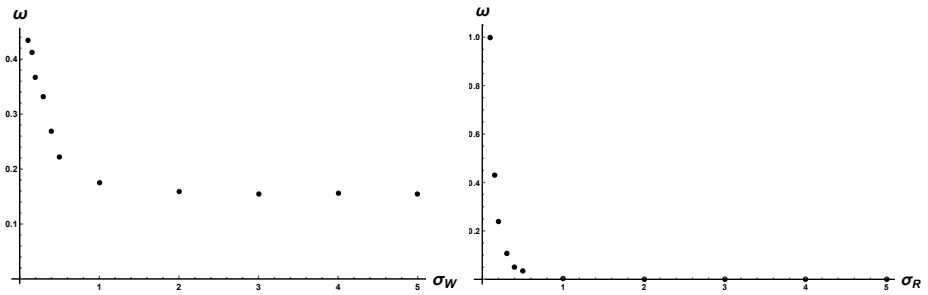
Note: Model specification taken from Cocco et al. (2005).

Optimal Portfolio-Choice We solve the model numerically using the Nelder-Mead algorithm. First, in the top panel of Figure 1, we vary labor income risk and asset return risk separately at ρ equaling zero. The risky share ω declines as the economic environment becomes more risky, be it from labor income risk σ_w or return risk σ_R. However, ω declines much faster when return risk σ_R rises. Second, in the bottom panel, we vary both dimensions of risk jointly, yet still keep ρ at zero. The plot demonstrates that, in the end, it is total risk, that determines portfolio choice.

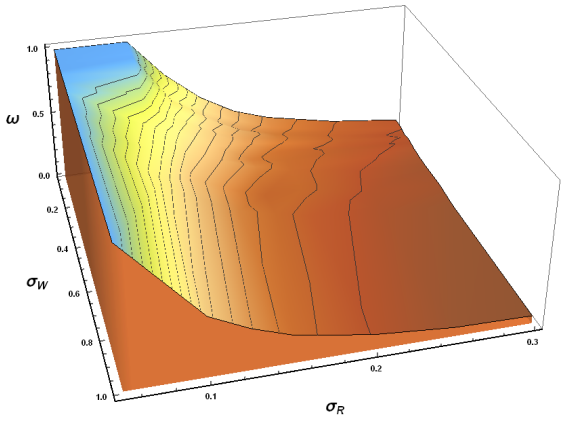
In Figure 2 we illustrate the importance of correlation between the two sources of risk. Although we have calibrated the correlation ρ to two relatively moderate values, i.e. 0.2 and -0.2[4], the change from the base case in Figure 1 is remarkable. Since now labor income risk and return risk are linked, the individual chooses far smaller risky portfolio shares at even moderate levels of risk when the correlation is positive. Conversely, the risks serve to hedge each other, which leads to a much higher risky share, if the correlation is negative.

In conclusion, we note that the two risk sources have non-trivial interactions that lead to diverse consumer behavior. Even at a correlation of zero, both risks contribute to the total risk and thus influence the choice of the risky portfolio share. When the correlation between the two risk sources is non-zero, the consumer's response is even more pronounced: at a moderate positive correlation, consumers completely eliminate risky assets from their portfolio. This occurs even at values of risk, that would have resulted in a positive risky share had the correlation been zero. Contrarily, a moderate negative correlation strongly incentivizes risky asset holdings since they offer insurance against labor market risk. These results point out that labor income risk and its co-movement with return risk are crucial for portfolio choice.

[4]Values chosen by Cocco et al. (2005).



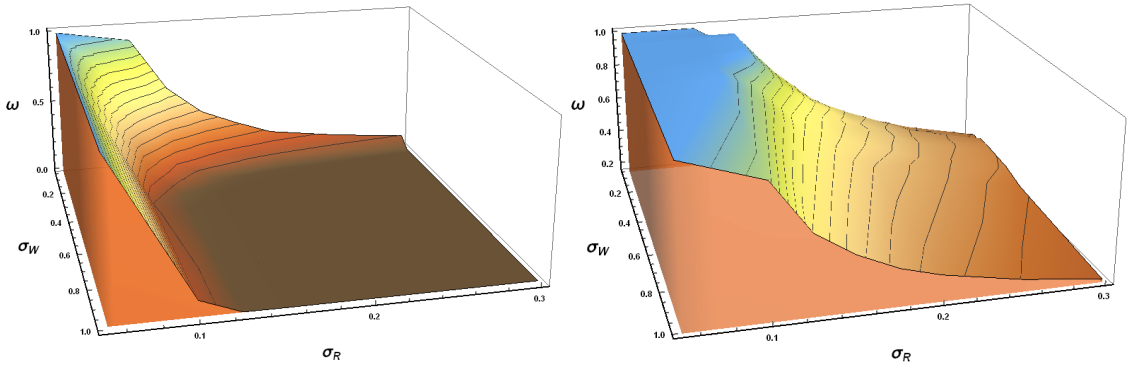
(a) Vary Risks Separately



(b) Vary Risks Jointly

Note: Authors' calculations using Mathematica 11. We plot the optimal share of risky assets for different σ_w and σ_R at $\rho = 0$.

Figure 1. Optimal Risky Share ω Varying Non-Asset Income Risk σ_w and Return Risk σ_R



(a) $\rho = 0.2$

(b) $\rho = -0.2$

Note: Authors' calculations using Mathematica 11. We plot the optimal share of risky assets for different σ_w and σ_R at ρ equal to -0.2 or 0.2.

Figure 2. Optimal Risky Share Varying Non-Asset Income Risk σ_w and Return Risk σ_R with Correlation ρ

3 Data

For our analysis we use two main data sources: the German Socio-Economic Panel and the Thomson Reuters Eikon database.

German Socio-Economic Panel We use the German Socio-Economic Panel (SOEP) as our primary source of data. The SOEP is a nationally representative panel study with data running from 1984 to 2018 (Goebel et al., 2019; Schröder et al., 2020). Data on assets, collected on the individual level, are available in 2002, 2007, 2012, and 2017, while data on labor market outcomes are available in every year.

Table 2. Observations: From the Full - to the Working Sample

	2002	2007	2012	2017	Sum
Full Dataset	23,892	20,869	27,940	32,397	105,098
Sample Restrictions					
Between 18 and 65	-4,066	-4,435	-5,296	-5,110	-18,907
Positive net wealth	-5,100	-4,166	-7,745	-12,612	-29,623
Full Labor Market Information	-10,029	-5,097	-9,421	-6,314	-30,861
Characteristics	-288	-373	-308	-657	-1,626
Working sample	4,409	6,797	5,170	7,704	24,081

Note: Compiled by the authors using SOEP v35. The table provides number of observations of full dataset and the working sample by year. The Table also shows, how several sample restrictions reduce the numbers of individuals in the dataset. The numbers of observation are based on imputed data.

Sample Definition We restrict the sample to the working population aged 18 to 65, who hold positive net wealth, with sufficient observations to construct the risk measure, the regressors, and the instrumental variable. We include four waves since data on assets is only available for 2002, 2007, 2012, and 2017. We provide an overview of the numbers of observations in Table 2. The restriction on the working population reduces the dataset by 18,907 observations. A large reduction is imposed by including only individuals with positive net wealth, eliminating another 29,623 observations. We choose to exclude those observations for two reasons: first, our analysis focuses on the financial share, which can only be observed for those who own some assets. Second, we exclude those with negative net wealth, mainly to keep our results comparable to the previous literature (Fagereng et al., 2018).[5] Focusing on individuals with full labor market information reduces the sample by another 30,861 observations. This includes individuals, which are employed long enough to provide information on wage volatility[6] and its correlation with financial market returns. Moreover, for the calculation of the instrument, we need information on their occupation (ISCO-88 code), and their residency (NUTS2, Nomenclature of Territorial Units

[5]This affects in total about 3,200 observations with financial assets. Including those observations, however, does not affect our results.

[6]For the construction of wage risk we use the years from 1998 to 2017.

for Statistics). As we control for a set of socio-economic characteristics in our regression analysis, we lose some observations due to missing values and limited panel information. Our basic working sample includes 24,081 observations.

Mean values for some of the labor market variables as well as socioeconomic characteristics are shown in Table A1 in Appendix A for both our working sample and the overall dataset in the considered years. Our sample selects on those who own at least some financial wealth and are in the labor force. Individuals in our working sample are more educated. Moreover, there are proportionally less women in the sample. The average number of children and the average age is around the same level in both samples. There are more married individuals, as our definitions potentially restricts younger singles, who do not hold financial wealth. There are less individuals with a migration background and slightly more individuals who live in former East Germany. Individuals in our working sample earn higher levels of gross labor income, and have higher net and financial wealth. There are also more individuals who own their own home. We also provide the financial share, with and without housing wealth.

Financial Market Returns We retrieve annual excess returns from the Thomson Reuters Eikon database. The returns are calculated as mean total return of the German HDAX index, which combines the main German indices, i.e. DAX, MDAX and TecDAX. To retrieve the excess return, we subtract mean annual interest rates of 10-year German sovereign bonds from the mean total HDAX returns. These excess return should capture the main volatility in German equity markets. The mean annual excess return is 6.01% with a standard deviation of 24.34% over the 1998-2017 period. A graph depicting mean annual returns per year is depicted in Appendix D in Figure A2.

Focal Variables Three types of information from the SOEP are central to our analysis: hourly wages, to construct the idiosyncratic variance, wealth portfolios, to construct the financial portfolio share, and fine-grained regional information, to construct the instrumental variable.

Wages—To compute hourly wages, we use reported monthly labor income and contractual working hours per week. A common concern with hourly wages constructed from survey data is measurement error. While it is not clear how measurement error would affect our estimates, we can allay these concerns by pointing out that measurement error of hourly wages has been studied in the SOEP before.[7] Caliendo et al. (2018) provide a cross-validation of SOEP-based distributions of working hours, monthly labor income, and hourly wages with the cross-sectional Structure of Earnings Survey (SES). SES is a firm-level survey dataset providing payroll information including income and contractual working hours. Caliendo et al. (2018) show that SOEP-based and SES-based distributions of income, working hours, and hourly wages are very similar, thus suggesting no relevant differences.

[7]Since we are ultimately only interested in the effect of idiosyncratic wage variance on the financial portfolio share, it is not clear that measurement error, if it were present to a noticeable extent, will affect this relationship in a meaningful way. Since we use an IV-strategy for our main estimates, measurement error should not be a problem in any case.

Financial Portfolio Share—The SOEP surveys a total of eight types of assets in 2017:

1. owner-occupied residential property,
2. miscellaneous property ownership (including undeveloped land and holiday and weekend homes),
3. financial assets (savings accounts, savings bonds, corporate stocks, and fund shares),
4. assets from private insurance policies (life and private pension insurance including Riester pensions),
5. balance on savings account with a building and loan association,
6. business assets (ownership of sole proprietorships and participation in partnerships or corporations, net operating liabilities),
7. tangible assets in the form of valuables such as gold, jewelry, coins, or artwork,
8. value of vehicles.

SOEP reports four types of liabilities

1. mortgage loans on owner-occupied property,
2. mortgage loans on miscellaneous property,
3. consumer loans,
4. student loans.

Figures on the value of vehicles and the balance of student loans were not collected between 2002 and 2012. To produce internally consistent wealth concepts, we exclude these items from the analysis.[8] Deducting the liabilities from the assets results in the total net wealth. Our financial portfolio share is constructed from gross financial assets divided by overall gross wealth excluding housing wealth.

Regional Identifiers—The SOEP records the current location of an individual's residence at different levels of aggregation down to the "Kreis"-level (NUTS3), comparable to a district. We use the level of aggregation above the "Kreis"-level, the NUTS2 code. This code is based on 38 "Regierungsbezirke", which translates to governmental districts.

4 Methodology

In the following we detail the calculation of the idiosyncratic wage variances and their correlation with financial market returns on the individual level, the definition of the financial share, and finally the construction of our instrumental variable.

[8] Vehicles can be argued not to be relevant to wealth, since they are a consumption good and act as a poor store of value. Education loans are almost completely irrelevant in Germany (Schröder et al., 2020).

Residual Wage Variance and Correlation To remove variation in wages that is predictable by the individual, we run the OLS regression:

$$w_{it} = \alpha + \rho w_{it-1} + \gamma' \tilde{\mathbf{X}}_{it} + e_{it}, \tag{4}$$

where w_{it} are log hourly wages in year t of individual i, $\tilde{\mathbf{X}}_{it}$ is a set of control variables containing a quadratic in age and dummies for the survey year, gender, company size, German federal states, employment history (unemployment, part-time, full-time), migration background, and completed education.[9] The term e_{it} contains idiosyncratic wage innovations.[10] We run this regression for the years 1998 to 2017. The estimates of the unexplained residuals $\hat{e}_{it}$ serve to calculate the idiosyncratic variance as

$$V_{it} = \frac{1}{4} \sum_{n=t-4}^{t} \hat{e}_{in}^2. \tag{5}$$

Thus, V_{it} are four-year rolling-window means of squared differences for each individual (cf. Fagereng et al., 2018).

To calculate individual-level correlations, we use the excess returns series from the German HDAX:

$$C_{it} = \frac{\frac{1}{4}\sum_{n=t-4}^{t}(\hat{e}_{in}) \times \left(ER_n - \frac{1}{4}\sum_{k=t-4}^{t} ER_k\right)}{\sqrt{V_{it}}\sqrt{Var(ER_t)}}, \tag{6}$$

where $Var(ER_t)$ is an analogously defined rolling-window variance of excess returns from the German HDAX.

Financial Portfolio Share The SOEP does not ask individuals directly for what they consider to be risky investments. However, we can calculate the share of the portfolio invested in financial assets. Thus, we define the financial portfolio share as:

$$fs_{it} = \frac{fa_{it}}{gw_{it}}, \tag{7}$$

where fa_{it} is the stock of financial assets, and gw_{it} is gross wealth, that is the sum of all assets, excluding housing wealth. By choosing the financial portfolio share, instead of the risky financial share, which is the more frequently used concept in the literature, we may encounter some discrepancies compared to other studies: a decrease (increase) in the

[9] This specification follows Fagereng et al. (2018) in the choice of controls. Unlike them, we include the lagged dependent directly in the specification and do not restrict ρ to one.

[10] Note that by restricting our attention to wage variance, instead of all of labor income, we are not threatening, but rather enhancing identification. Our primary focus is on identifying the transmission parameter that tells us how changes in background risk affect the financial portfolio share. By focusing on hourly wages, we are eliminating one important source of potentially contaminating variation not due to background risk, i.e. variation in hours of work.

overall financial portfolio share may occur due to a reduction (increase) in risky assets or a reduction (increase) in non-risky assets. While our outcome measures differs from the the risky portfolio share, our results on subjective economic worries support the argument that people are reacting on the risky financial margin. Further, it appears that the SOEP question on financial assets is formulated in a way to reduce the likelihood that individuals report wealth in sight accounts or other non-risky investments. The questionnaire specifically asks for "Geldanlagen", i.e. financial investments, which suggests that these types of assets are at least to somewhat risky.

We exclude housing wealth because it is not only an investment decision, but rather a joint consumption and investment decision. Further, housing is not easily liquidated. The macroeconomic literature has recognized that there are "wealthy hand-to-mouth" households that cannot liquidate their housing wealth in reaction to shocks to smooth consumption (Weidner, 2014). Hence, we expect that housing is not easily liquidated or adjusted to react to changes in background risk. The return on housing wealth, especially in Germany, is far less volatile than the return on equity. Data from Jordà et al. (2019) and a calculation using this data in König et al. (2020) support this fact.[11] Thus, when we include housing wealth as a non-risky/non-financial asset and reproduce our main results in Appendix E, our main conclusions are qualitatively unaffected.

Empirical Strategy In a first step, we wish to measure the effect of idiosyncratic wage risk on the financial portfolio share. Following Fagereng et al. (2018), we model the relationship with a linear equation as

$$fs_{it} = \alpha + \beta V_{it} + \gamma' \mathbf{X}_{it} + \nu_i + \epsilon_{it}, \tag{8}$$

where V_{it} is the idiosyncratic wage variance measure in Eq (5), the set of control variables $\mathbf{X}_{it}$ contains a quadratic in age, dummies for household composition and marriage, survey year, home-ownership, as well as the log of net wealth. Further, ν_i is a fixed effect, which will capture time-invariant differences in portfolio choice behavior, e.g. individual-level heterogeneity in risk preference. ϵ_{it} is an error that captures time-varying unexplained changes in the financial share. The coefficient of interest is β.

In a second step, we wish to measure the effect of the correlation of wage risk with financial market returns on the financial share. The specification takes the form

$$fs_{it} = \alpha + \beta_1 V_{it} + \beta_2 C_{it} + \gamma' \mathbf{X}_{it} + \nu_i + \epsilon_{it}, \tag{9}$$

where C_{it} is the correlation measure in Eq. (6) now the coefficients of interest are β_1 and β_2.

[11] While returns to housing wealth are far less volatile, the risk exposure for the individual is possibly far greater because the investment is indivisible and diversification within housing is not possible for most individuals.

For both equations we run regressions with fixed effects and fixed effects along with instrumental variables.

Instrumental Variables We deal with the omitted variable problem by estimating Eq. (8) with fixed effects. Only the problem of measurement error in the idiosyncratic variance remains. The concern is that some of the variance will be due to individuals' choices (Fagereng et al., 2018). Thus, background risk is measured with error and, as Fagereng et al. (2018) show, leading to an estimate of the effect on portfolio choice that is biased toward zero.

A valid instrument captures a part of the variance that individuals cannot meaningfully influence. Our IV-strategy exploits the interactions of fine-grained regional, time, and occupational indicators (2-digit ISCO code) to form cell-specific deviations from the overall variance, i.e. a group IV estimator (Blundell et al., 1998; Blau and Kahn, 2006; Burns and Ziliak, 2017). This IV captures variation in local labor market conditions, such as plant closures and openings or different developments in regional infrastructure, which cannot be influenced to a meaningful extent by the individual. Therefore, the variation we use for our IV is comparable to the IV strategy established in Fagereng et al. (2018), which relies on firm-specific productivity shocks and links them to workers in these firms. To check whether the IV is relevant, we report F-statistics of the first stage in the IV regressions.

The regional classification uses the SOEP's NUTS2 variable, which is one level above the finest regional information, i.e. the "Kreis"-level (NUTS3). We choose this level to achieve a balance between granularity and thus more variation on the one hand, and sample size within each of the groups on the other. We then interact the regional dummies with time dummies and occupational dummies to obtain our final dummy set. The number of groups used to construct the IV is 3,427 and the mean group size is 15.44 (s.d. 13.06).[12]

One could be concerned that at low group size, the cell mean is driven by one or a couple of observations with a particularly high wage variance. However, we are estimating a fixed effects IV regression, so that persistent individual level differences are controlled for. Thus, the dynamics of the cell means drive the variation of the IV.

To construct the instrument for the variance, we run a regression of V_{it} on the group indicators and the prediction from this regression is the IV. Similarly, since we also need an IV for the correlation with financial market returns, we run an analogous regression and prediction for C_{it}. Thus, we have exactly one instrument for each of the endogenous variables.[13]

5 Results

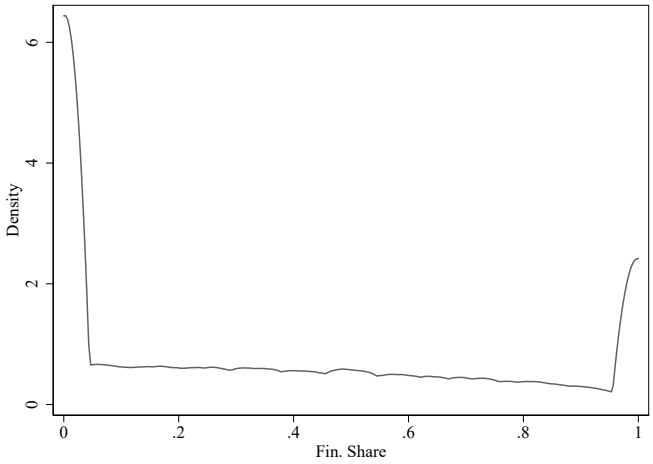
We begin by showing descriptives for our focal variables and then present the results from our regression analysis.

[12] In Appendix B we show more descriptive statistics.

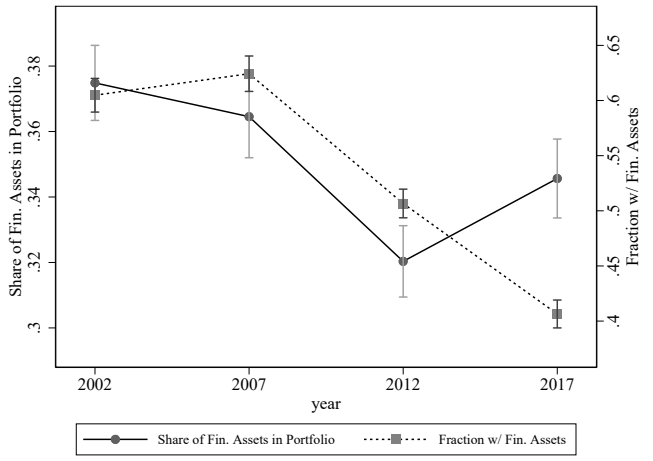
[13] This means, even though, the variation is based on many cell means, we collect them in one variable. Therefore we have no overidentifying restrictions.

5.1 Descriptives

As a first description of our dataset, we illustrate the distribution and dynamics of the financial share and we show its kernel density estimate and the movement of its mean over time in Figure 3.



(a) Kernel Density of the Financial Share



(b) Mean of the Financial Share and Fraction of Observations with some Financial Assets Over Time

Note: Compiled by the authors using SOEP v35. The kernel density was calculated with a bandwidth of 0.02. Unweighted means in panel (b) are provided with 95 percent confidence intervals based on bootstrapped standard errors using 1000 replicate weights. Sample is not restricted to working sample.

Figure 3. Descriptive Statistics on the Financial Share

The patterns for both the density and the time-series line up closely with what is found for the risky financial portfolio share in the comparable literature (Fagereng et al., 2018). Inspecting the upper panel, we find that a very large fraction of observations have no financial assets at all. For low financial shares—smaller than 20%—the fraction of observations is still considerable. For financial shares larger than 40% the fraction of observations is very small with a final, considerable hump at 100%.

The lower panel shows the share of observations with financial assets, which ranges around 60% to almost 40%. The share dropped considerably after 2007 to levels around 40% in 2017. The conditional financial share dropped since 2002 (about 37%), with a pronounced decrease after the financial crisis of 2008, and a recovery to pre-crisis levels in 2017 (about 34%). The financial share comoves with the number of observations with positive financial asset holdings.[14]

In Table 3 we show basic descriptives of the focal variables for the working sample. The average financial share in the working sample is about 33%, while the standard deviation is quite large. The average idiosyncratic wage variance is large compared to measures of the idiosyncratic income variance presented in Fagereng et al. (2018), which may be due to institutional differences between Norway and Germany. The average correlation is close to zero and the standard deviation is comparatively large. The descriptive statistics of all variables do not vary much over the years, but they show plenty of variation in the focal variables in the working sample.

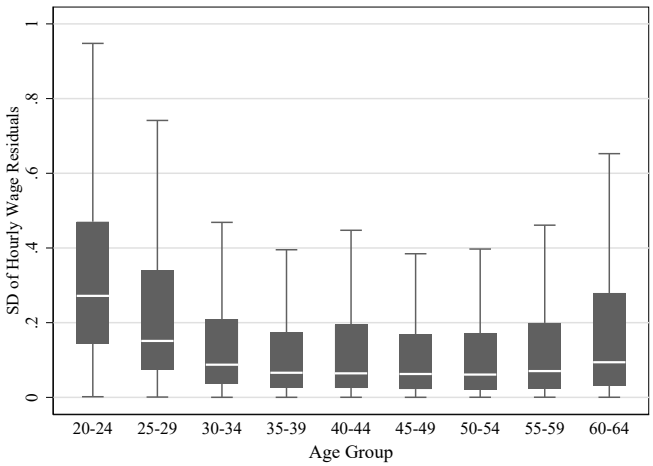
Table 3. Descriptives of Focal Variables for the Full Working Sample

Variable	year	mean	SD	min	max
Financial Share	2002	0.339	0.366	0	1
	2007	0.329	0.350	0	1
	2012	0.326	0.351	0	1
	2017	0.316	0.360	0	1
Residual Wage Variance	2002	0.217	0.383	0.0002	5.324
	2007	0.205	0.370	0.0002	5.694
	2012	0.192	0.342	0.0002	4.371
	2017	0.198	0.353	0.0003	4.460
Correlation	2002	-0.090	0.585	-1	1
	2007	-0.006	0.565	-1	1
	2012	0.071	0.539	-1	1
	2017	-0.036	0.553	-1	1

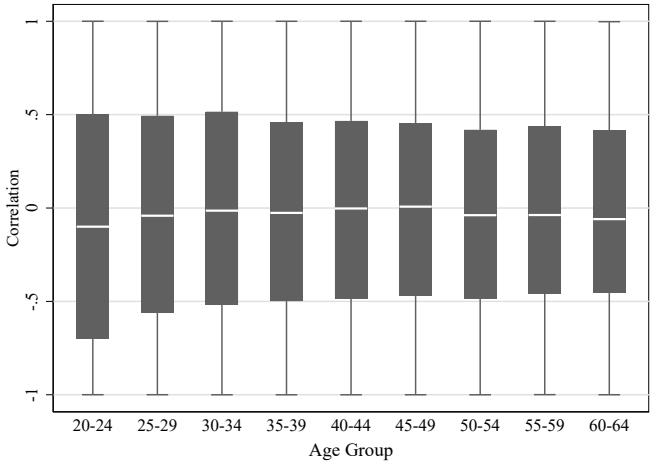
Compiled by the authors using SOEP v35. The table provides unweigthed means of the focal variables for every year of the sample.

We provide box plots of the standard deviation of wage risk and its correlation with financial market returns for five year age groups in Figure 4. The standard deviation is higher for younger age cohorts, remains at a lower level for the middle aged and slightly increases for the groups closer to retirement. This is what we would expect, indicating individuals face higher unexplained wage volatility at the beginning of their career (Kaplan, 2012). Increasing experience combined with high human capital individuals entering the labor force at the end of their education reduces the standard deviation during the 20s and 30s. More individuals dropping out of the labor force and devaluation of human capital partially explain the dispersion before retirement. The correlation with HDAX returns,

[14]The fraction of households with financial assets does not equal the stock market participation rate. Other studies suggest that the participation rate in Germany lies between 18 percent (Breunig et al., 2019) and 24 percent (Necker and Ziegelmeyer, 2016).



(a) Box Plot of Standard Deviation of Wage Risk by Age Cohorts.



(b) Box Plot of Correlation Between HDAX Returns and the Idiosyncratic Wage Risk by Age Cohorts.

Note: Compiled by the authors using SOEP v35. The white bar in the box represents the median. The ends of the boxes represent the 25th and 75th percentile, respectively. The whiskers define the adjacent value, which is the first (third) quartile minus (plus) 1.5 times the interquartile range. Sample is to working sample

Figure 4. Life Cycle Pattern of Wage Risk and Correlation

however, does not show any connection to age cohorts. The median is about constant and close to zero, while the quartile ranges, as well as the adjacent values, reveal large dispersion.

5.2 The Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share

Table 4 shows the causal effect of wage risk and the correlation of wage risk with financial returns on the financial portfolio share.

Table 4. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0288***	-0.0839**	-0.0288***	-0.0845**
	(0.0097)	(0.0332)	(0.0097)	(0.0332)
C_{it}			0.0023	0.0059
			(0.0049)	(0.0131)
age	-0.0299***	-0.0312***	-0.0298***	-0.0311***
	(0.0037)	(0.0038)	(0.0037)	(0.0038)
age^2	0.0003***	0.0004***	0.0003***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
home ownership	-0.0494***	-0.0483***	-0.0493***	-0.0481***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)
log wealth	-0.0166***	-0.0168***	-0.0166***	-0.0168***
	(0.0044)	(0.0044)	(0.0044)	(0.0044)
constant	1.1771***	1.2208***	1.1770***	1.2210***
	(0.0849)	(0.0892)	(0.0849)	(0.0892)
Controls	Yes	Yes	Yes	Yes
Obs.	24081	24081	24081	24081
Fstat		78.2542		78.2542

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. FE is a fixed effects specification, IVFE is an instrumental variables fixed effects specification. Log wealth refers to the log of net wealth. Fstat refers to the first stage F-statistic. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns (1) and (2) in Table 4 regress the financial portfolio share on wage risk showing that the coefficient of the wage variance is negative and statistically significant at least at the 5%-level in all specifications. Note that the coefficient roughly triples in absolute size when switching from the FE to the IVFE specification.

Our baseline estimate is in column 2, the IVFE specification. Taking this value, we find that increasing wage risk by one standard deviation decreases the financial share by roughly 3 percentage points.[15] Comparing this value to the existing literature, we find that it is on the upper end of recent estimates being close to the coefficient in Betermier et al. (2012) (-0.12). However, as we have detailed in Section 4, our dependent variable is the financial share of the portfolio and not the risky share. Thus, while the financial share

[15]Note that this calculation is only ultimately meaningful for behavior if it refers to uninsurable wage variance, which we cannot fully disentangle from insurable wage variance.

is closely aligned with the risky share, we expect the effect of wage risk on the financial share to be a lower bound of the effect of wage risk on the risky share.[16]

We choose control variables that are familiar to the literature, but since our dependent variable is the financial portfolio share, coefficients and interpretations are not necessarily aligned. Our age effect is u-shaped and reverses around age forty, the prime age for home ownership and family formation. After forty, we find an increasing trend in the financial share, since individuals are more likely to save for retirement. The log of net wealth is negatively associated, pointing to the fact that individuals with very high values in wealth do not have a large financial asset share. This is in line with common observations in the SOEP data that very high-wealth individuals hold their assets primarily in their own businesses (Schröder et al., 2020). Home ownership also enters negatively. This corresponds, in a broader sense, with Chetty et al. (2017), who find that less wealth invested in housing would increase liquid wealth. Further, as individuals in Germany often build (financial) wealth to buy a house, it is not surprising that after this purchase their financial share drops.

Columns (3) and (4) of Table 4 additionally include the correlation of wage risk with financial asset returns. In the FE-specification the coefficient is small and positive, while it is larger in the IVFE-specification. However, in both specifications the correlation is statistically insignificant and one order of magnitude smaller than the wage risk effect. Thus, we do not find any evidence that the correlation influences individuals' portfolio choices.

5.3 Discussion

The regression analysis yields two central findings.

1. The effect of wage risk on the financial portfolio share is negative and statistically significant, and the effect sizes are comparable to those found in the existing literature.

2. The effect of the correlation of wage risk with financial asset returns on portfolio choice are economically and statistically insignificant.

The first result confirms the basic qualitative pattern in the literature: more wage risk leads to less investment in financial assets. The second results is completely novel. The estimated effect of the correlation is close to zero and statistically insignificant. Our suspicion is that, wage risk is perceived intuitively by individuals, but the correlation with financial market returns is not. As individuals observe wage changes, some of those changed not being in line with their expectations, they can develop an intuitive understanding of their wage risk (Guvenen, 2007). Hence, it seems plausible that this understanding would also influence their portfolio choice. For example, if a worker unexpectedly receives a lower wage because demand for the product she is producing has dropped, it seems reasonable that she would lower her exposure to financial market risks.

[16] Since we control for net wealth, we do not suspect that we are picking up primarily movements in the denominator of the financial portfolio share.

For the correlation, a case for intuitive understanding appears weak. Developing any understanding, let alone an intuitive one, of the correlation of wage risk with financial market returns is much less natural and cannot develop as individuals observe the realizations of their wages alone. Rather, it would take explicit calculation to know how one's wage moves with the markets. Accordingly, we suspect that the small and insignificant coefficient on the correlation stems from insufficient salience of it.

Our argumentation would fail, if German portfolio investments were rather internationally diversified and, therefore, do not take German equity market volatility into account. This is unlikely, as the literature confirms a persistent home bias in investment decisions (Levy and Levy, 2014). Moreover, the volatility of international financial markets is smaller, but correlates highly with the internationally integrated German equity market[17]: even if investors would diversify their portfolios only internationally, the risk would correlate similarly with their wage risk. Another possibility is that financial market returns and wage risk do not comove enough. The descriptive statistics in Table 3 and Figure 4 point to considerable variation in the correlation across the working sample. Thus, it seems unlikely that the issue arises due to a lack of variation or a concentration on zero. In the next subsection we take a look at whether wage variance and correlation are perceived differently.

5.4 The Influence of Wage Risk on Economic Worries

To see whether wage risk and its correlation with financial asset returns are perceived with different degrees of salience, we exploit a variable in the SOEP that asks people to report their worries about their own financial or economic conditions on a three point Likert scale (1=strongly worried, 2=somewhat worried, 3=not worried). We perform OLS and IV regressions of this index of worries on the wage variance and the correlation with financial asset returns. Again, we use the IV regressions to account for the measurement error problem. Moreover, we control for the same socio-economic characteristics as in the analysis above. Table 5 shows the results.

In both the OLS and IV specifications the wage variance coefficient is sizable, statistically significant and negative, thus, pointing to an increase in worries. When the IV specification is run—just like in Table 4—the size of the coefficient increases strongly in absolute terms. The coefficient of the correlation with financial asset returns, however, is positive in both specifications, not significant in either one, and close to zero in both. These results support the hypothesis that individuals perceive wage risk and factor it into their assessment of economic worries, but they do not take the correlation with financial market returns into account.

[17] See Appendix D.

Table 5. The Influence of Wage Risk and its Correlation with Asset Returns on Economic Worries

	(1) OLS	(2) IV	(3) OLS	(4) IV
V_{it}	-0.1389***	-0.2214***		
	(0.0124)	(0.0294)		
C_{it}			0.0049	0.0093
			(0.0073)	(0.0196)
age	-0.0375***	-0.0407***	-0.0322***	-0.0322***
	(0.0034)	(0.0036)	(0.0034)	(0.0034)
age^2	0.0004***	0.0004***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
home ownership	-0.0797***	-0.0810***	-0.0776***	-0.0776***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)
log wealth	0.1028***	0.1037***	0.1012***	0.1012***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
constant	1.9926***	2.0707***	1.8621***	1.8631***
	(0.0729)	(0.0770)	(0.0721)	(0.0722)
Controls	Yes	Yes	Yes	Yes
N	24,013	24,013	24,013	24,012
Fstat		73.4197		454.6992

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IV is an instrumental variables specification. Log wealth refers to the log of net wealth. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Robustness Checks

We provide several robustness checks for our results. They include variations of the primary fixed effects IV model specification and a jackknife procedure to test for sensitivity of the IV estimates to single groups in the group IV.

Variations of Model Specification and Sample Selection Table 6 shows the coefficients of wage risk V_{it} and the correlation C_{it} for several different specifications of the fixed effects IV specification. The full results of our different specifications are provided in Appendix E. Column (1) shows the specification without any controls, column (2) includes age controls only, column (3) presents the results when including wealth controls only, column (4) increases the rolling-window of the wage and return variances from 4 to 5, column (5) excludes self-employed workers, and column (6) excludes civil servants from the sample.

The table shows that our results are robust to different model specifications. The effect size of the instrumented residual wage variance ranges between -0.109 and -0.071 and generally stays significant at the 5%-level. The correlation, however, remains close to zero and non-significant.

Excluding the self-employed in column (5) is an important robustness check for two reasons. First, the self-employed often invest a large share of their wealth in their own business and invest little in financial markets (Fossen, 2011; Fossen et al., 2020). Second,

wage risk is different for this group, especially because the self-employed may more freely choose their hours and may choose to forgo lower their wage in favor of re-investing in their business (Hurst et al., 2010).

We exclude individuals working as civil servants in column (6) because they are typically less affected by local labor market conditions. The estimated coefficient of the wage variance is −0.109, and thus more negative than in the baseline specification. This is not surprising, as we exclude a group which faces less wage risk.[18]

In Appendix E, we also provide the results of including household wealth into the financial share definition. Table A11 shows that the IVFE estimates of V_{it} and C_{it} are smaller and become non-significant at the 5%-level. As the change of the financial share represents now higher amounts of wealth, the results point to the same direction, even though they are not significant at the 5%-level. As we argue above, we do not think that it is appropriate to consider housing wealth in the context of short-run portfolio choice decisions.

Table 6. Robustness Checks: Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share

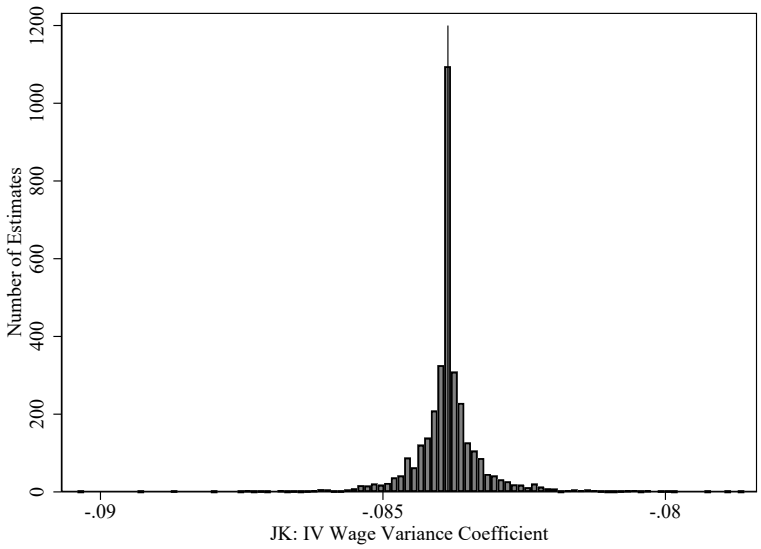
	(1)	(2)	(3)	(4)	(5)	(6)
	No Controls	Age Controls	Wealth Controls	5 years Rolling Window	Excluding Self-Employed	Excluding Civil Servants
V_{it}	-0.0713**	-0.0879***	-0.0742**	-0.0885**	-0.0811*	-0.1091***
	(0.0329)	(0.0335)	(0.0327)	(0.0412)	(0.0453)	(0.0376)
C_{it}	-0.0081	0.0068	-0.0043	-0.0001	0.0023	0.0039
	(0.0127)	(0.0132)	(0.0126)	(0.0155)	(0.0140)	(0.0158)
Obs.	24,081	24,081	24,081	24,081	22,742	17,611
Fstat	510.59	90.94	259.63	65.53	54.57	56.27

Compiled by the authors using SOEP v35. The table provides the coefficients of the wage variance V_{it} and correlation C_{it} of the fixed-effects IV regression with the financial share as dependent variable. Specification (4) to (6) include the same control variables as the main specification in our analysis. Full regressions are provided in Appendix E in Tables A5 to A10. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

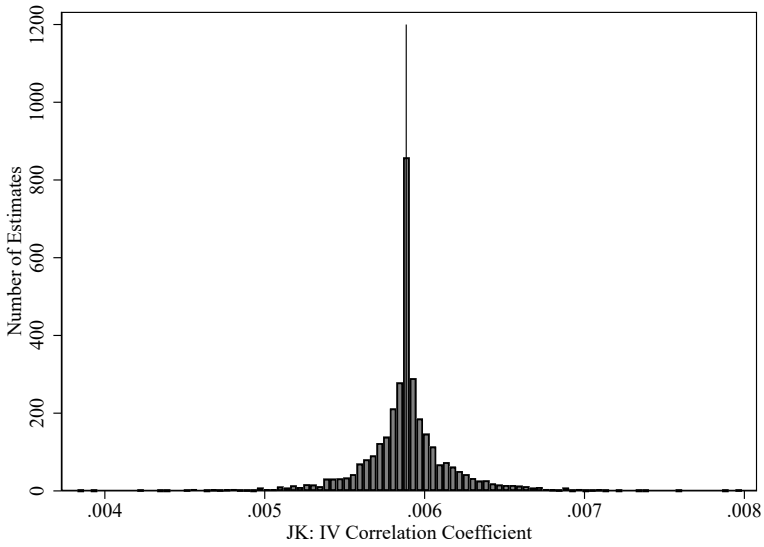
Jackknifing IV Groups We test the sensitivity of our IV estimates to the systematic exclusion of single groups. Therefore, we re-run our main regressions while eliminating one group at a time. As we exclude every group once in this procedure, we obtain 3,427 estimates of the instrumented idiosyncratic wage risk, i.e. β_1 from Eq. (8), and the effect of the correlation of wage risk with financial market returns volatility, β_2 from Eq. (9), on the financial portfolio share.

Figure 5 provides the histograms of the 3,427 coefficients estimates. The upper panel provides the coefficient of the instrumented residual wage variance on the x–axis and the number of estimates on the y–axis. The histogram shows, that our point estimate of −0.0845, provided as vertical line, is confirmed by more than 1,000 estimates while the variation of the estimates is small. The lower panel provides the coefficient of the instrumented correlation on the ordinate, and, again, the point estimate of 0.0059 does not vary strongly.[19] We conclude from this that our results do not depend on single groups of the instruments.

[18] The mean value of V_{it} for civil servants is 0.13 compared to 0.21 of the overall working sample.
[19] We provide further descriptive statistics of the jackknifed results in Table A12 in Appendix E.



(a) Jackknife Results: Instrumented Residual Wage Risk



(b) Jackknife Results: Instrumented Correlation

Note: Compiled by the authors using SOEP v35. The panels provide the histograms of the jackknifed estimates of β_1 from Equation 8 (upper panel), and β_2 from Equation 9 (lower panel). The y-axis depicts the number of estimates. The solid line represents the original point estimate. The bin size is 100.

Figure 5. Histograms of Jackknife Results

7 Conclusion

We have shown a relationship between wage risk and portfolio choice in Germany. We find that an increase of idiosyncratic wage volatility by one standard deviation reduces the financial portfolio share by three percentage points, while the correlation between financial market returns and idiosyncratic wage volatility is economically and statistically insignificant. Individuals with non-zero correlation do not appear to adjust their wealth portfolios by taking correlation into account, even though standard portfolio choice theory predicts this. We believe that this is due to a lack of salience and support this claim by regressing an index of individuals' economic worries on idiosyncratic wage volatility and its correlation with financial market risk. This exercise shows that individuals with more wage risk worry more about their economic situation, but the correlation shows no such association.

Given the effect the correlation has on the optimal portfolio, our empirical result on the correlation is worrying. Depending on the sign and size of the correlation, individuals face either more or less risk than they are aware off, leading to large investment mistakes. Informing individuals about the correlation structure of their wage risk with financial market returns could either reduce their risk level for a given return or help in using the hedging mechanism to maximize returns at a given risk level. However, our study is limited: we cannot quantify the extent of these investment mistakes, because we do not observe total background risk. Thus, we also cannot quantify the extent to which these mistakes impact individual welfare, which leaves it as a route for promising future research.

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A Descriptive Statistics of Full - and Working Sample

Table A1. Descriptives for the SOEP

Variable	Sample	Full
Years of education	13.10	11.78
	(1.05)	(0.19)
Female in %	47.2	52.4
	(0.18)	(0.04)
Number of children	0.69	0.70
	(0.36)	(0.07)
Age	45.47	46.07
	(0.04)	(0.01)
Married in %	70.0	62.5
	(0.16)	(0.04)
Migration backgr. in %	13.3	22.9
	(0.12)	(0.03)
Living in East in %	22.8	21.4
	(0.16)	(0.03)
Gross Labor income	3,050	2,224
	(9.32)	(1.81)
Net Wealth	145,266	102,668
	(2,035)	(909)
Financial wealth	17,808	14,033
	(331)	(146)
Home-ownership in %	61,5	47,2
	(0.18)	(0.04)
Financial Share without Housing	32,6	41,2
	(0.13)	(0.09)
Financial Share with Housing	18,9	17,4
	(0.10)	(0.05)

Note: Compiled by the authors using SOEP v35. The table provides the unweighted mean values for the Sample and Full dataset *Sample* describes our working sample with the working population aged 18 to 65 in the years 2002, 2007, 2012, and 2017. *Full* describes the complete dataset in these 4 waves. Bootstrapped standard errors, calculated by using 500 replica weights, are provided in parentheses.

B Descriptive Statistics of the Instrumental Variable Groups

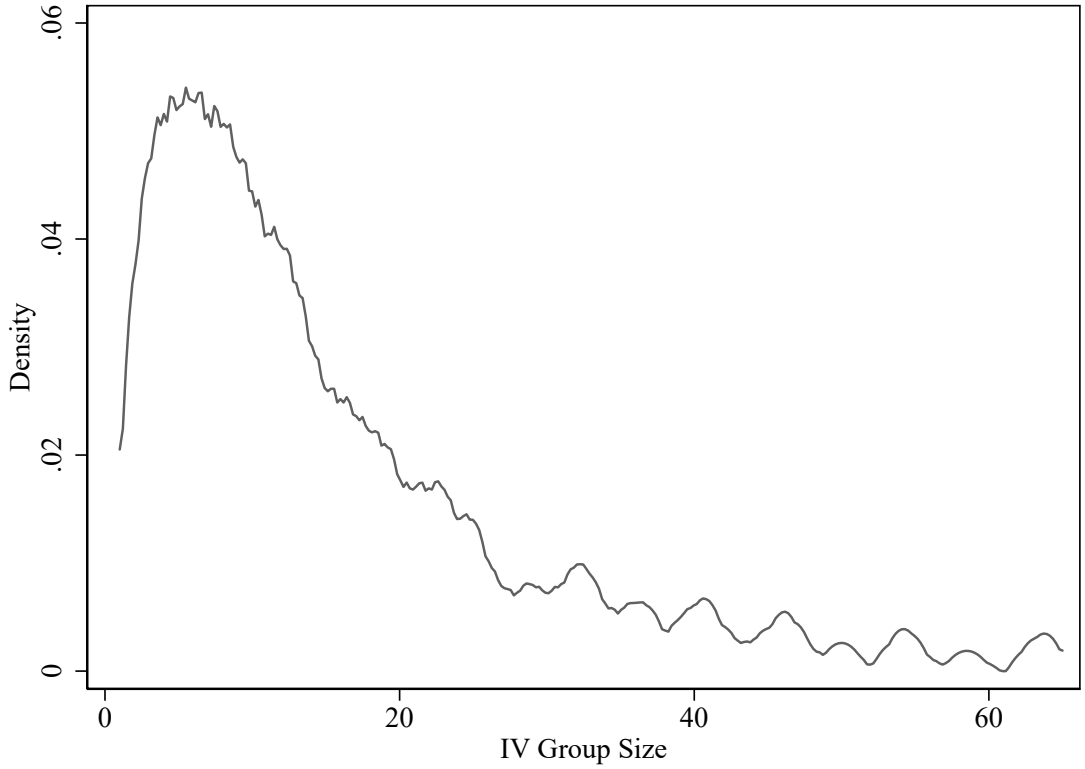

Figure A1. Kernel Density of the IV Group Size

Note: Compiled by the authors using SOEP v35. The kernel density was calculated with a bandwidth of 0.8.

Table A2. IV Group Sizes

Man	SD	p25	p50	p75	p90	N
15.44	13.06	6	11	20	34	3,427

Compiled by the authors using SOEP v35. Table provides descriptive statistics on the group size.

C Descriptive Statistics of the Instrumental Variable Groups

Table A3. Sample Comparison: Owners and Non-Owners of Financial Assets

	owners	non-owners	p-value
Residual Wage Variance	0.194	0.262	0
Years of Educ.	13.29	11.47	0
Female	0.512	0.533	0.01
Number of Children	0.695	0.970	0
Age	44.55	39.90	0
Married	0.662	0.576	0
East	0.207	0.210	0.139
Risky Assets	26,296	0	0
N	34,328	44,506	

Note: Compiled by the authors using SOEP v35. Means of variables and p-values of t-tests. Sample is not restricted to working sample.

Table A4. Descriptives of Focal Variables for the Full Working Sample

	fs_{it}	V_{it}	C_{it}
mean	0.326	0.202	-0.015
sd	0.356	0.361	0.562
min	0	0.0002	-1
max	1	5.694	1
N		24,081	

Compiled by the authors using SOEP v35.

D Excess returns over time

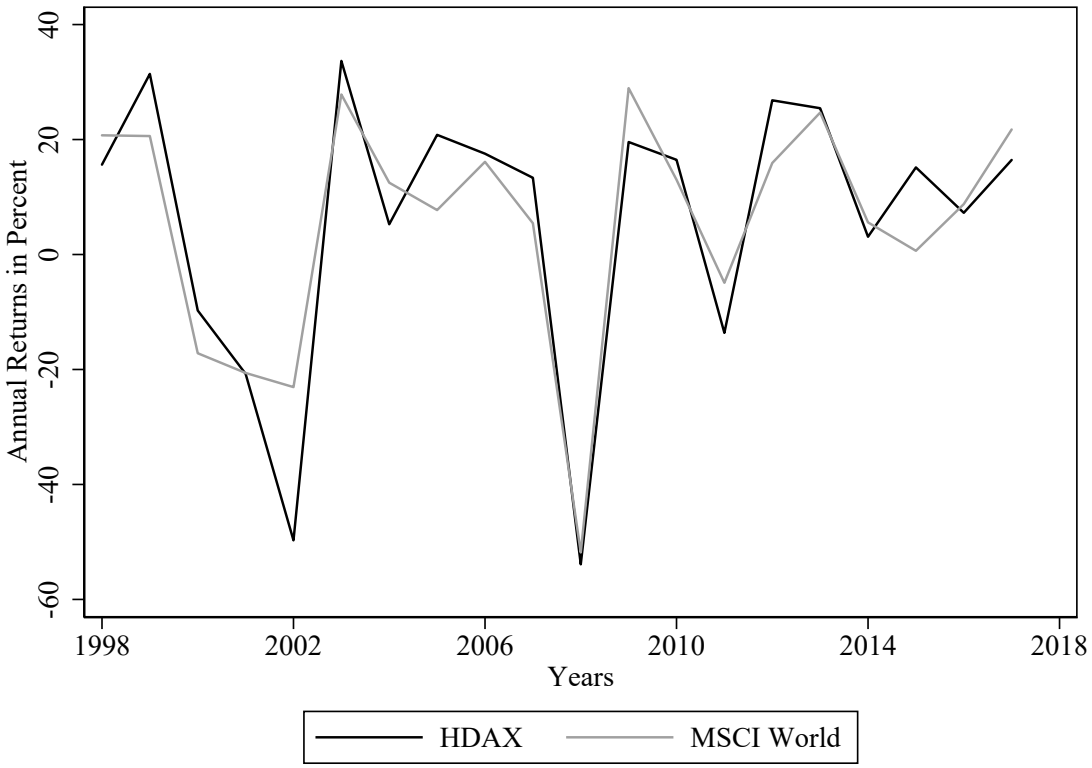

Figure A2. Excess returns

Note: Compiled by the authors using Thomson Reuters Eikon Database. The excess return is calculated by substracting the interest rates of the 10-years German sovereign bond.

E Robustness Checks

Table A5. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: No Control Variables.

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0191*	-0.0718**	-0.0191*	-0.0713**
	(0.0100)	(0.0329)	(0.0100)	(0.0329)
C_{it}			0.0019	-0.0081
			(0.0050)	(0.0127)
constant	0.3297***	0.3404***	0.3297***	0.3402***
	(0.0020)	(0.0067)	(0.0020)	(0.0067)
Obs.	24,081	24,081	24,081	24,081
Fstat		513.36		513.36

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IVFE represents the instrumental variables specification. Log wealth refers to the log of net wealth. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: Only Age Controls

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0294***	-0.0871***	-0.0294***	-0.0879***
	(0.0098)	(0.0334)	(0.0098)	(0.0335)
C_{it}			0.0027	0.0068
			(0.0049)	(0.0132)
age	-0.0346***	-0.0360***	-0.0345***	-0.0359***
	(0.0036)	(0.0037)	(0.0036)	(0.0037)
age^2	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
constant	1.1167***	1.1614***	1.1165***	1.1614***
	(0.0815)	(0.0857)	(0.0815)	(0.0857)
Obs.	24,081	24,081	24,081	24,081
Fstat		90.94		90.94

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IV is an instrumental variables specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: Only Wealth controls

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0210**	-0.0744**	-0.0210**	-0.0742**
	(0.0098)	(0.0327)	(0.0098)	(0.0327)
C_{it}			0.0020	-0.0043
			(0.0049)	(0.0126)
home ownership	-0.0597***	-0.0590***	-0.0596***	-0.0591***
	(0.0119)	(0.0119)	(0.0119)	(0.0119)
log wealth	-0.0179***	-0.0184***	-0.0179***	-0.0184***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
constant	0.5590***	0.5755***	0.5591***	0.5751***
	(0.0409)	(0.0424)	(0.0409)	(0.0424)
Obs.	24,081	24,081	24,081	24,081
Fstat		259.63		259.63

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IV is an instrumental variables specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: 5 Years Rolling Average

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0294***	-0.0885**	-0.0294***	-0.0885**
	(0.0108)	(0.0412)	(0.0108)	(0.0412)
C_{it}			0.0003	-0.0001
			(0.0058)	(0.0155)
age	-0.0299***	-0.0315***	-0.0299***	-0.0315***
	(0.0037)	(0.0039)	(0.0037)	(0.0039)
age^2	0.0003***	0.0004***	0.0003***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
home ownership	-0.0494***	-0.0484***	-0.0494***	-0.0484***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)
log wealth	-0.0167***	-0.0169***	-0.0167***	-0.0169***
	(0.0044)	(0.0044)	(0.0044)	(0.0044)
constant	1.1794***	1.2300***	1.1794***	1.2300***
	(0.0851)	(0.0925)	(0.0851)	(0.0926)
Obs.	24,081	24,081	24,081	24,081
Fstat		65.53		65.53

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IVFE represents the instrumental variables specification. Log wealth refers to the log of net wealth. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: Excluding Self-Employed Individuals

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0253**	-0.0807*	-0.0253**	-0.0811*
	(0.0114)	(0.0452)	(0.0114)	(0.0453)
C_{it}			0.0013	0.0023
			(0.0052)	(0.0140)
age	-0.0296***	-0.0310***	-0.0296***	-0.0310***
	(0.0039)	(0.0041)	(0.0039)	(0.0040)
age^2	0.0003***	0.0004***	0.0003***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
home ownership	-0.0545***	-0.0535***	-0.0544***	-0.0534***
	(0.0130)	(0.0130)	(0.0130)	(0.0130)
log wealth	-0.0150***	-0.0153***	-0.0150***	-0.0153***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
constant	1.1596***	1.2058***	1.1595***	1.2060***
	(0.0887)	(0.0968)	(0.0887)	(0.0968)
Obs .	22,742	22,742	22,742	22,742
Fstat		54.58		54.58

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IVFE represents the instrumental variables specification. Log wealth refers to the log of net wealth.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: Excluding Civil Servants

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0241**	-0.1084***	-0.0242**	-0.1091***
	(0.0104)	(0.0373)	(0.0104)	(0.0376)
C_{it}			0.0035	0.0039
			(0.0060)	(0.0158)
age	-0.0267***	-0.0283***	-0.0267***	-0.0283***
	(0.0045)	(0.0046)	(0.0045)	(0.0046)
age^2	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
home ownership	-0.0638***	-0.0625***	-0.0637***	-0.0624***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)
log wealth	-0.0179***	-0.0178***	-0.0179***	-0.0178***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)
constant	1.1138***	1.1701***	1.1135***	1.1702***
	(0.1029)	(0.1066)	(0.1029)	(0.1066)
Obs .	17,611	17,611	17,611	17,611
Fstat		55.27		55.27

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IVFE represents the instrumental variables specification. Log wealth refers to the log of net wealth.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11. Influence of Wage Risk and its Correlation with Asset Returns on the Financial Portfolio Share: Including Housing Wealth in the Financial Share Definition.

	(1) FE	(2) IVFE	(3) FE	(4) IVFE
V_{it}	-0.0160	-0.0229	-0.0160	-0.0233
	(0.0082)	(0.0243)	(0.0082)	(0.0243)
C_{it}			0.0057	0.0039
			(0.0038)	(0.0100)
age	-0.0226***	-0.0228***	-0.0226***	-0.0228***
	(0.0031)	(0.0032)	(0.0031)	(0.0032)
age^2	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
home ownership	-0.1659***	-0.1658***	-0.1658***	-0.1657***
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
log wealth	-0.0459***	-0.0459***	-0.0459***	-0.0459***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
constant	1.2288***	1.2342***	1.2283***	1.2342***
	(0.0749)	(0.0780)	(0.0749)	(0.0779)
Obs.	24,081	24,081	24,081	24,081
Fstat		84.01		84.01

Compiled by the authors using SOEP v35. Robust standard errors in parentheses. IVFE represents the instrumental variables specification. Log wealth refers to the log of net wealth.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12. JK: IV estimates

Variable	mean	sd	p25	p50	p75	p90
V_{it}	-0.0846	0.0007	-0.0848	-0.0846	-0.0845	-0.0841
C_{it}	0.00294	0.0003	0.00284	0.00294	0.00302	0.00324

Compiled by the authors using SOEP v35. Table provides descriptive statistics on the group size.