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Investors' favourite –
A different look at valuing individual labour income

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Abstract Human capital is a key economic factor in both macro- and micro-economics, and, at least for most people, by far their largest asset. Surprisingly, relatively little effort has been undertaken in the extant literature to empirically determine the value of individual human capital. This paper aims at closing the gap. We use the Substantial-Gain-Loss-Ratio to calculate Good Deal bounds for securitizations of individual labour income one year ahead. We evaluate the attractiveness of hypothetical human capital contracts using US data and can thereby identify investors' favourites.

Keywords Human Capital Contracts, Asset Pricing, Substantial-Gain-Loss-Ratio
JEL: G12, J17, C58

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1 Introduction

The role of human capital in economics is crucial. However, economic research usually investigates its aggregated form, thereby adopting a purely macroeconomic perspective or rather a viewpoint necessary to examine economy wide asset pricing models. This approach does neither mirror human capital's heterogeneity, nor individual risk sufficiently. In particular, human capital is, at least for most people, by far the largest asset they possess. In the US, human capital constitutes between 50 and 90 percent of households' overall wealth (Palacios (2015), Baxter and Iermann (1997), Lustig et al. (2013)). If we were dealing with a traditional financial asset, individuals would therefore certainly try to diversify the resulting cluster risk. One (theoretical) possibility to diminish individual income risk is given by human capital contracts, a form of securitizing individual labour income, or other income dependent assets such as certificates on corresponding income indices.

Since income dynamics are risky in the long run, such human capital contracts are attractive for individuals, especially for students.[1] The importance of this area for financial investors has been outlined by Shiller (2003) and Huggett and Kaplan (2016). Moreover, Voelzke (2016) shows that returns on human capital evolve distinctively different to those of stocks for most individuals, making them attractive for investors as a new asset class to diversify their portfolio.[2]

Huggett and Kaplan (2012) offer a thorough review of the relevant literature on the pricing of human capital contracts in general, and on the valuing of aggregated human capital in particular. Thereby note, that the human capital claim behaves differently to exchange traded assets, such that a simple combination of existing market prices, i.e. a factor pricing model, is no reasonable approach to pricing. Therefore, Huggett and Kaplan (2011) derive explicit price bounds for individual human capital by analyzing the joint distribution of financial assets held by individuals and their labour income. They specify an individual stochastic discount factor (SDF) and derive price limits for human capital contracts, by using so called Good Deal bounds.[3] These Good Deal bounds are price intervals formed by precluding prices that are escessively attractive with respect to a performance measure. In particular, Huggett and Kaplan (2011) apply the well-known Sharpe ratio to narrow price intervals.

In contrast, our approach uses the Gain-Loss-Ratio, i.e. the ratio of expected stochastically discounted gains and expected stochastically discounted losses, and its advancement the Substantial-Gain-Loss-Ratio (SGLR) as performance measure.[4] More so, our procedure enables the inclusion of an arbitrary asset

[1] See Shiller (2003) for the general advantages for the individual, Palacios (2002) for the special circumstances and historical examples of student financing and Heese and Voelzke (2017) for an example where unexpected technological change in the form of the internet is shown to alter income dynamics significantly.

[2] Further, see Diesteldorf et al. (2016), who emphasize financial investors' need to find new - possibly bubble-free - asset classes to invest in.

[3] Cochrane (2000) develops the corresponding theory and introduces applications.

[4] Cp. Bernardo and Ledoit (2000) and Voelzke (2015) concerning both GLR and SGLR.

pricing model as the underlying pricing mechanism. Thus, opposed to Huggett and Kaplan (2011), we adopt the viewpoint of a financial market, i.e. instead of investigating an individual's value for human capital, we aim at determining its hypothetical market value.

The starting point for the approach are the two fundamental equations for asset pricing given by[5]

$$\begin{aligned} p_t &= E[m_{t+1}x_{t+1}] \\ m_{t+1} &= f(\text{data, parameters}), \end{aligned}$$

where p_t equals the asset price at time t, m_{t+1} the SDF, and x_{t+1} the uncertain payoff. Thereby, fully specifiying the SDF (by an underlying model) allows to calculate explicit prices of arbitrary assets. In contrast, for no-arbitrage models, the SDF is not fully known but is assumed to be consistent with observed prices. Thus, in the latter models, prices are only narrowed to no-arbitrage bounds, whereas the former models usually fail to empirically fit prices on overall markets.[6]

Owing to this fact, we strike a balance between both pricing paradigms by proposing the use of Good Deal bounds based on the (S)GLR, and a freely chosen asset pricing model. Attractiveness is then measured depending on the corresponding SDF. In the application, we use a SDF of a consumption-based asset pricing model, representing parts of the fundamental pricing mechanism. Thereby note that one of the key advantages of the (S)GLR approach is its ability to incorporate misspecified asset pricing models without losing its validity. The better the SDF is specified, the better the pricing becomes, i.e. the intervals get thinner.

For the actual price calculations we require a joint predictive distribution of both individual income and SDF. Therefore, we model individual income dynamics in line with Huggett and Kaplan (2011) and Huggett and Kaplan (2012), and capture the key components, i.e. an age effect, an individual specific effect, and an idiosyncratically persistent and transitory component. As such, our work reflects the standard of the extant literature on the matter, see Lillard and Weiss (1979) and Guvenen (2009). However, while Huggett and Kaplan (2011) exploit the co-movement of stock returns and aggregated income, our approach captures the occupation specific interdependency via the consumption based SDF. This allows to additionally investigate the heterogeneity between occupational groups which Voelzke (2016) detects for income dynamics of German employees. In particular, we model the consumption dynamics by a VAR model of macroeconomic variables and include consumption into the income panel model as an exogenous variable. Thereby note that we estimate the model in a Bayesian manner, such that the joint predictive distribution incorporates the full estimation uncertainty. Moreover, the required attractiveness limit for asset prices is set by examining the observed financial markets. Eventually, we provide price

[5] Cp. Cochrane (2001) p. xv.

[6] See Ludvigson (2011) for an overview of various asset pricing models and their empirical evaluation.

intervals as Good Deal bounds based on the observed SGLR limit and the estimated joint predictive distribution of individual labour income and SDF. Given the price intervals and the expected payoff, we furthermore calculate expected returns for hypothetical human capital contracts.

In comparison to Huggett and Kaplan (2011), our procedure is more robust, as misspecifications of the underlying models are allowed for and reflected in the price intervals. The occupation specific estimation of the co-movement between SDF and individual labour income explores the differences in attractiveness and increases the pricing and estimation precision. Eventually, we get tighter return intervals, even though we take into account the idiosyncratic risk and the full predictive density.

Our paper proceeds as follows: Section 2 describes the methodology employed. Section 3 outlines our empirical results, and Section 4 concludes.

2 Methodology

We calculate price intervals for a hypothetical human capital contract which securitizes individual labour income for the next year ahead. The resulting uncertain payout is priced by precluding all values that make the generating assets too attractive. Following this idea, we model and estimate the joint behaviour of individual labour income and all factors that influence the chosen measure. Here, this necessitates setting up a model for income and macroeconomic movements. Subsequently, we pick an appropriate attractiveness measure and determine an attractiveness limit on the observed market. Next, we use this limit and the joint distribution of individual labour income and SDF to calculate the Good Deal bounds by the SGLR.

2.1 Determination of an Attractiveness Limit

One of the recent developments in the research area of Good Deal bounds is the SGLR as developed in Voelzke (2015). It overcomes certain drawbacks of the GLR proposed by Bernardo and Ledoit (2000), which leads to a pricing approach that is regarded as the unification of model based and no-arbitrage asset pricing. The starting point for calculating the GLR is an arbitrary SDF, e.g. implied by a fully specified asset pricing model. Subsequently, price bounds based on the GLR can be calculated by finding all prices that imply a GLR smaller than a certain limit. Varying the attractiveness limit from one to infinity corresponds to sliding from pricing based on a fully specified SDF with a unique price to no-arbitrage asset pricing yielding no-arbitrage bounds. Thus, we would like to stress that the (S)GLR is an especially advantageous valuation method if the pure SDF is known to be misspecified. Owing to this insight, we use a particularly simple consumption-based approach to construct the benchmark SDF. Thus, our results can be interpreted as a lower bound regarding the price interval width.

Following Cochrane (2001) we define the SDF as

$$m_t \propto \left(\frac{c_t}{c_{t-1}}\right)^{-3}, \tag{1}$$

where c_t denotes consumption and the risk aversion parameter is assumed to equal 3. Subsequently, we use historic market and consumption data to determine the maximally and minimally observed SGLR. Therefore, we calculate the discrete Substantial-Gain-Loss-Ratio (dSGLR) with the algorithm developed in Voelzke and Mentemeier (2016). It is defined as

$$\mathrm{dSGLR}^{M}_{\beta,k}(X) \;:=\; \inf_{m' \in \mathrm{dSDF}^k_\beta} \frac{\sum_{i=1}^{Tk} (m'_i x_{(\mathrm{i \ mod \ T})})^+}{\sum_{i=1}^{Tk} (m'_i x_{(\mathrm{i \ mod \ T})})^-}, \tag{2}$$

where $1-\beta$ quantifies the substantial part, k is a grid-thinning parameter, X a vector of payouts, M a vector of corresponding SDFs and dSDF^k_β a set of discrete SDFs that are close to the SDFs in M.[7] Moreover, the operators $(\cdot)^+$ and $(\cdot)^-$ denote the absolute value of a positive and negative number, respectively. We calculate (2) for different markets and use the minimal and maximal values as attractiveness limits a_l and a_u, respectively.

2.2 Labour Income Panel Model

Given the attractiveness limits, we require the joint distribution of the SDF and individual labour income to calculate price intervals using the SGLR. We propose the following model as data generating process

$$\begin{aligned}
y_{i,t} &= \alpha_i + \varphi\, age_{i,t} + \delta\, age^2_{i,t} + \gamma_k\, \Delta c_t + z_{i,t} + u_{i,t},\\
z_{i,t} &= \rho\, z_{i,t-1} + \epsilon_{i,t},\\
\epsilon_{i,t} &\sim \mathcal{N}(0, \sigma^{z\,2}_i),\\
u_{i,t} &\sim \mathcal{N}(0, \sigma^{u\,2}_i),
\end{aligned}$$

where $y_{i,t}$ is the logarithmized labour income of individual i at time t, and $age_{i,t}$ is the age of individual i, and $u_{i,t}, \epsilon_{i,t}$ are error terms that are assumed to be independently identically normally distributed. Additionally, we introduce the growth rate of logarithmized consumption Δc_t as exogenous variable to capture the dependency of labor income and SDF.

Furthermore, α_i is an individual parameter determining the general wage level. This parameter picks up all individual properties, such as skills or residence, that affect wage. ρ governs the persistence of the long-run shocks $z_{i,t}$. It is expected to be close to one, since wage processes usually experience several

[7] For a detailed explanation and motivation see Voelzke and Mentemeier (2016) and the references therein.

strongly persistent shocks. φ and δ control the influence of age on income. This is common for most models of labour income dynamics.[8] Including the quadratic form captures the observation that wages increase more strongly in the early years of the working life, while typically growing less closer to retirement. Last, γ_k quantifies the co-movement of income and consumption growth, which is key for the proposed pricing procedure. In order to gain statistical power, we model this parameter occupation specific, i.e. $k = 1, \dots, K$ indexes the occupational affiliation of individual i.

2.3 Estimation Approach

We estimate the model parameters and the density of the joint distribution of all individual incomes $y_{i,t+1}$ and Δc_{t+1} with a Bayesian approach. For parsimony, we simplify notation by defining the sets of parameters

$$\begin{aligned}
\alpha &= \{\alpha_1, \dots, \alpha_n\}, \\
\sigma^u &= \{\sigma_1^u, \dots, \sigma_n^u\}, \\
\sigma^z &= \{\sigma_1^z, \dots, \sigma_n^z\}, \\
\gamma &= \{\gamma_1, \dots, \gamma_K\}.
\end{aligned}$$

Moreover, we define the full parameter set $\theta = \{\varphi, \delta, \rho, \gamma, \alpha, \sigma^z, \sigma^u\}$, denote the set θ less φ as $\theta_{-\varphi}$, and proceed analogously for all other sets. Additionally we summarize the incomes at time t as $Y_t = \{y_{1,t}, \dots, y_{n,t}\}$ and denote the full set of observations as $\mathbf{Y} = \{Y_t, \dots, Y_T\}$. Thus, the posterior distribution of the parameters is given by the density

$$p(\theta|\mathbf{Y}) \propto p(\mathbf{Y}|\theta)p(\theta), \tag{3}$$

where the first term is the likelihood of data $\mathbf{Y}$ and the second term the joint prior density of θ. Note that we assume independent priors, such that the joint prior distribution of θ can be factorized into one-dimensional distributions.

Our approach to sampling from the posterior distribution (3) does not assume conjugate distributions. Instead, we make extensive use of the Metropolis-Hastings (MH) algorithm. In particular, our sampling approach uses five large Gibbs blocks, such that we iteratively sample from the conditional posteriors

1. $p(\varphi, \delta|\theta_{-\{\varphi,\delta\}}, \mathbf{Y})$,
2. $p(\rho|\theta_{-\rho}, \mathbf{Y})$,
3. $p(\gamma|\theta_{-\gamma}, \mathbf{Y})$,
4. $p(\alpha|\theta_{-\alpha}, \mathbf{Y})$,
5. $p(\sigma^u, \sigma^z|\theta_{-\{\sigma^u,\sigma^z\}}, \mathbf{Y})$,

where in the last two blocks, additional Gibbs steps are used to sample the individual parameters α_i, σ_i^u and σ_i^z.

[8] E.g. Lillard and Weiss (1979) and Guvenen (2009).

To carry out the sampling algorithm, we need to evaluate the likelihood conditioned on different sets of parameters. As the latent variable $z_{i,t}$ does not allow to calculate any likelihood directly, we apply a canonical Kalman filter, which enables us to evaluate any required log-likelihood as

$$\log p(\mathbf{Y}|\theta) = \log \prod_{i=1}^{n} p(y_{i,1}|\theta) + \sum_{t=2}^{T} \log \prod_{i=1}^{n} p(y_{i,t}|\theta, y_{i,t-1}),$$

as $u_{i,t}$ and $\epsilon_{i,t}$ are independent by assumption.

As our sampler has to cope with a large number of variables, the proposal distribution of the MH algorithm is of key importance. Therefore, we use an adaptive variant of the MH algorithm, which incrementally scales the variance of a normal proposal such that the acceptance ratio is close to 0.3 for all parameters. We begin to scale the proposal after a burn-in period of $N_b = 10000$ and stop scaling after $N_s = 50000$ iterations of the sampler. We use the subsequent $N = 50000$ draws as our posterior sample. Our estimation results are not driven by the priors as we use the uninformative uniform prior distributions defined in Table 1.

α	φ	γ	ρ	δ	σ^z	σ^u
$\mathcal{U}(-30, 30)$	$\mathcal{U}(0, 10)$	$\mathcal{U}(-20, 20)$	$\mathcal{U}(0.3, 1)$	$\mathcal{U}(-10, 0)$	$\mathcal{U}(0, 5)$	$\mathcal{U}(0, 50)$

Table 1 Prior Distributions. This table reports marginal prior distributions of θ, where $\mathcal{U}(a, b)$ denotes a uniform distribution in range of a to b.

Having obtained the posterior parameter draws, we sample from the predictive distribution of future income of all individuals with density

$$\prod_{i=1}^{n} p(y_{i,T+1}|\theta, \mathbf{Y}, z_{i,T+1}), \tag{4}$$

where the "predicted" age of individuals $i = 1, \ldots, n$ in $T + 1$ is obvious and the $z_{i,T+1}$ are drawn from the Kalman filtering distributions. However, we additionally require draws from the predictive density of log consumption growth. Therefore we adopt a Baysian VAR approach with Minnesota Prior to obtain a density forecast for consumption.[9] Moreover, besides the required samples of consumption growth, a sample M_{T+1} of the corresponding predictive density of the SDF is easily obtained by using equation (1).

2.4 Good Deal Bounds

Applying the aforementioned procedures results in a sample of the joint predictive distribution of individual labour income Y_{T+1} and SDF M_{T+1}, and observed

[9] We use a random-walk-in-levels prior for the constant. The freely chosen coefficients of the Minnesota Priors of the parameter covariance matrix are set to 0.5. Cp. Koop and Korobilis (2010) for further details of this approach.

upper and lower attractiveness limits a_u and a_l. Individual price intervals can now be established by solving the following equations for the lower and the upper price limit p_l and p_u, respectively

$$\mathrm{dSGLR}_{\beta,k}^{M_{T+1}}(\tilde{y}_{i,T+1} - p_l) = a_l,$$
$$\mathrm{dSGLR}_{\beta,k}^{M_{T+1}}(\tilde{y}_{i,T+1} - p_u) = a_u,$$

where $\tilde{y}_{i,T+1}$ are samples obtained from (4) and β and k are the dSGLR specific parameters described in Voelzke and Mentemeier (2016).[10]

3 Empirical Results

We use US data to price a hypothetical human capital contract and provide evidence for heterogeneous interval width and location vary between occupational groups and individuals. Moreover, even though we take into account the full distribution of the parameter estimates and use a more robust approach concerning model misspecification, the price intervals are tighter as in comparable approaches e.g. Huggett and Kaplan (2011).

In the following, we first briefly describe the data set and the estimation results before outlining our outcomes for the income model and the resulting price intervals.

3.1 Data

The data for the VAR model of consumption is taken from Mark W. Watson's Homepage.[11] We use the macroeconomic variables outlined in Smets and Wouters (2007), i.e.: GDP, GDP deflator, federal funds rate, consumption, investment, hours worked and wages in the USA. The federal funds rate is monthly data, whereas the other variables are quarterly data. Except for the federal funds rate, all data is logarithmized. We annualize the data and use observations from 1959 through to 1997 to calculate the density forecast of logarithmized consumption for the year 1998.

To obtain yearly individual labour income and occupation, we employ PSID[12] data from 1978 to 1997. We only include individuals with an uninterrupted income trajectory above 6000 Dollar per year that does not exhibit unrealistic

[10] We set $\beta := 0.01$ and $k := 1$, since we prefer to use a large sample from the predictive density instead of using a large k.

[11] Obtained from `http://www.princeton.edu/~mwatson/ddisk/hendryfestschrift_replicationfiles_April28_2008.zip` in December 2016.

[12] Panel study of income dynamics, public use dataset. Produced and distributed by the Institute for Social Research, University of Michigan, Ann Arbor, MI (2016). We use the data in the form stated by the Cross-national Equivalent File (cp. Burkhauser et al. (2000)).

outliers.[13] Moreover, we fix an individual's occupation to be the one that is most often stated over the years.

3.2 Estimation Results

The estimated VAR model yields a predictive density of log consumption growth with median 4.50, whereas the 2.5%- and 97.25%-quantile are 4.45 and 4.56 respectively. Note that these results are consistent with the true realization in 1998, which is 4.51.

Turning towards the income model, the parameter estimates for the common parameters are reported in Table 2. Complementary trace plots of the MH procedure and corresponding histograms are shown in Figure 2 in the appendix.[14]

The estimates for φ and δ with positive and negative signs show the expected behaviour. The positive effect of age on income decreases when individuals become older. The autoregressive parameter ρ is close to one, underlining the long run impact of the persistent shocks. Moreover, note that the occupation- and individual-specific parameters vary significantly (not reported here), mirroring heterogeneous income trajectories. In particular, γ_k differs across the K occupational groups, reflecting their different exposure to the economic overall movements. Thereby, a positive γ_k parameter renders a corresponding human capital contract unattractive for a representative investor. By tendency, the corresponding human capital contract pays more in good times and less in bad times. As a result, the corresponding price interval lies more to the left. The opposite behaviour, i.e. parallel co-movement with the SDF, means that the cash flow is attractive for a representative investor, resulting in intervals that tend to higher prices.

Parameter	Median	2.5% Quantile	97.5% Quantile
φ	0.1453	0.1369	0.1533
δ	-0.0010	-0.0011	-0.0009
ρ	0.9770	0.9656	0.9873

Table 2 Posterior Statistics. This table reports the median, the 2.5% and the 97.5% quantile of the posterior distribution of the common parameters φ, δ and ρ.

[13] We exclude trajectories that include observations of twice the individual's average income value.

[14] Note that the high correlation and autocorrelation of the chains from φ and δ do not harm our analysis. We base our prediction density and SGLR calculation on an i.i.d. draw from the posterior sample, which is equivalent to a thinning factor larger than 100.

3.3 Price Intervals

In order to calculate the price intervals based on the estimation results, we set the maximal attractiveness to 10.5 and the minimal value to 2.6.[15] Both values indicate attractiveness and imply that expected returns will tend to be positive even for assets with a moderate negative correlation to consumption risk. Table 3 summarizes the results for the largest occupational groups of our sample. We calculate return intervals by dividing the expected payout in 1998 by the upper and the lower price bound.

Occupational Code	Median Interval Width	Upper Bound	Lower Bound	# Obs.
`archit`	11.7%	25.8%	8.6%	32
`eng. Tech`	14.6%	23.4%	7.8%	13
`relatmed`	12.3%	19.7%	6.8%	31
`mathemat`	12.2%	19.5%	7.0%	17
`accounta`	8.8%	15.6%	5.4%	11
`educator`	6.7%	16.3%	6.0%	54
`scientis`	9.1%	15.7%	5.3%	13
`security`	9.8%	18.8%	7.3%	13
`inspecto`	12.4%	24.4%	9.3%	18
`convey`	10.6%	21.7%	7.1%	15
`transpor`	16.1%	25.1%	9.3%	45
`labor/cr`	11.2%	19.5%	6.5%	20

Table 3 Price Intervals. This table reports the median return interval width, average upper and lower return bounds for different occupational groups with the corresponding number of observations (# Obs.) for occupations with more than ten individuals in the data sample.

Augmenting the results for occupational groups, we provide a histogram of the logarithmized interval lengths across all individuals in Figure 1. It visualizes the overall distribution of interval widths and outlines the individual-specific risk on human capital returns. In particular, the price interval widths of individual income trajectories cover a range from a few percent up to 60% and more. Moreover, Figures 3 - 5 in the appendix visualize estimation results for three exemplary individuals. They differ with respect to their variance value and its decomposition between the persistent and transient shocks, most clearly reflected in their historic income trajectories.

[15] This corresponds to the observed values of the 1%-dSGLR for major total return indices of the S&P500. In particular, we investigate the total index returns of the energy, finance, industry, consumer staples, information technology, materials, health care and telecommunication services sector and the S&P500 composite itself between 1989 and 2015. Financial data is taken from Thomson Reuters Datastream; consumption data is provided by the U.S. Bureau of Economic Analysis, retrieved from the homepage of the FRED, Federal Reserve Bank of St. Louis.

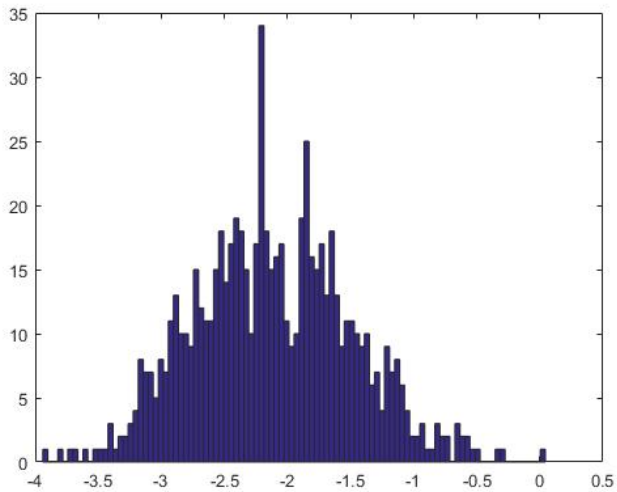

Fig. 1 Histogram of Logarithmized Return Interval Widths. This figure reports the cross section of individual interval widths of the data sample in log units.

4 Conclusion

Our paper develops and conducts a new approach to calculating price intervals for individual labour income, all the while accounting for model misspecification and estimation uncertainty. We incorporate a consumption-based asset pricing approach and adopt the viewpoint of a market representing investor. In particular, pooling by occupational groups enables us to identify the differences in attractiveness of various occupational groups and their individuals as assets for financial investors. Eventually, we state tighter price intervals in comparison to existing approaches in the literature.

Inclusion of an employment dummy into the model to quantify unemployment risk and using a more advanced asset pricing model is left for further research.

References

Baxter, M. and U. J. Iermann (1997). The international diversification puzzle ls worse than you think. *The American Economic Review 87*(1), 170–180.

Bernardo, A. E. and O. Ledoit (2000). Gain, loss, and asset pricing. *Journal of Political Economy 108*(1), 144–172.

Burkhauser, R. V., B. A. Butrica, M. C. Daly, D. R. Lillard, and R. V. Burkhauser (2000). The cross-national equivalent file.

Cochrane, J. H. (2000). Beyond arbitrage: Good-deal asset price bounds in incomplete markets. *The Journal of Political Economy 108*(1), 79–119.

Cochrane, J. H. (2001). Asset pricing, 2001.

Diesteldorf, J., S. Meyer, and J. Voelzke (2016). New evidence for explosive behavior of commodity prices. *Working Paper*.

Guvenen, F. (2009). An empirical investigation of labor income processes. *Review of Economic dynamics 12*(1), 58–79.

Heese, C. and J. Voelzke (2017). Labour income in the age of internet revolution. *The Empirical Economics Letters 16*, 73–81.

Huggett, M. and G. Kaplan (2011). Human capital values and returns: Bounds implied by earnings and asset returns data. *Journal of Economic Theory 146*(3), 897–919.

Huggett, M. and G. Kaplan (2012). The money value of a man. Technical report, National Bureau of Economic Research.

Huggett, M. and G. Kaplan (2016). How large is the stock component of human capital? *Review of Economic Dynamics 22*, 21 – 51.

Koop, G. and D. Korobilis (2010). *Bayesian multivariate time series methods for empirical macroeconomics*. Now Publishers Inc.

Lillard, L. A. and Y. Weiss (1979). Components of variation in panel earnings data: American scientists 1960-70. *Econometrica: Journal of the Econometric Society*, 437–454.

Ludvigson, S. C. (2011). Advances in consumption-based asset pricing: Empirical tests. Technical report, National Bureau of Economic Research.

Lustig, H., S. Van Nieuwerburgh, and A. Verdelhan (2013). The wealth-consumption ratio. *Review of Asset Pricing Studies 3*(1), 38–94.

Palacios, M. (2002). Human capital contracts.

Palacios, M. (2015). Human capital as an asset class implications from a general equilibrium model. *Review of Financial Studies 28*(4), 978–1023.

Panel study of income dynamics, public use dataset. Produced and distributed by the Institute for Social Research, University of Michigan, Ann Arbor, MI (2016).

Shiller, R. J. (2003). *The new financial order: Risk in the 21st century.* Princeton University Press.

Smets, F. and R. Wouters (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *The American Economic Review 97*(3), 586–606.

Voelzke, J. (2015). Weakening the gain–loss-ratio measure to make it stronger. *Finance Research Letters 12*, 58–66.

Voelzke, J. (2016). Individual labour income, stock prices and whom it may concern. *Applied Economics Letters*, 1–4.

Voelzke, J. and S. Mentemeier (2016). Computing the substantial-gain-loss-ratio. *Working Paper*.

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Appendix

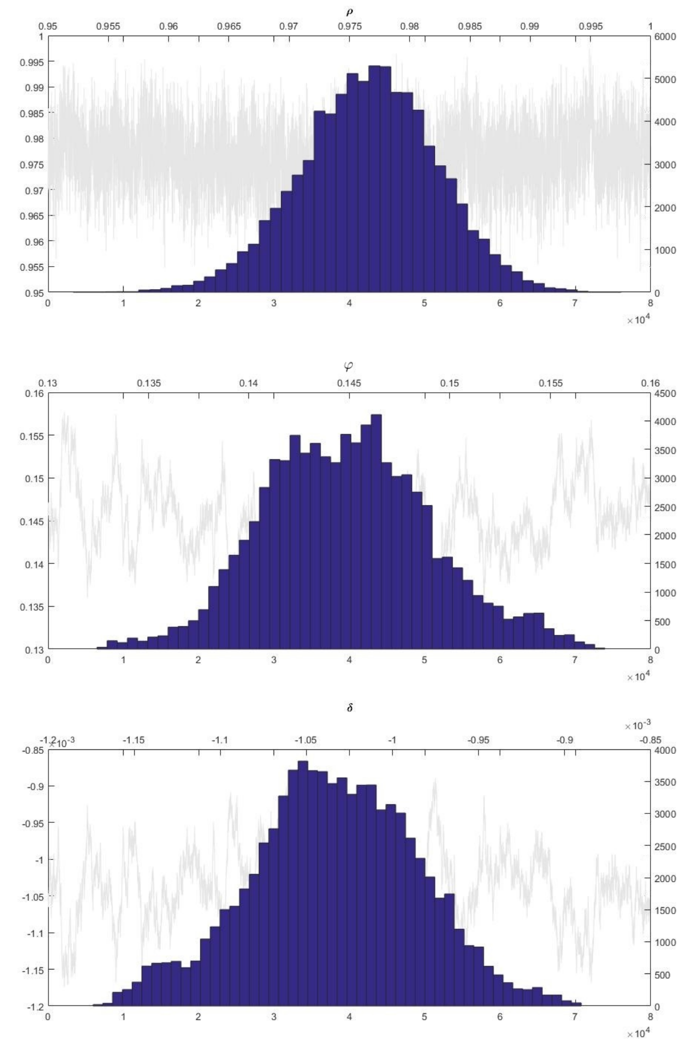

Fig. 2 Posterior Distributions. This figure provides histograms (blue) and the trajectory of the corresponding Markov Chain (light grey) of the common parameters ρ, φ and δ.

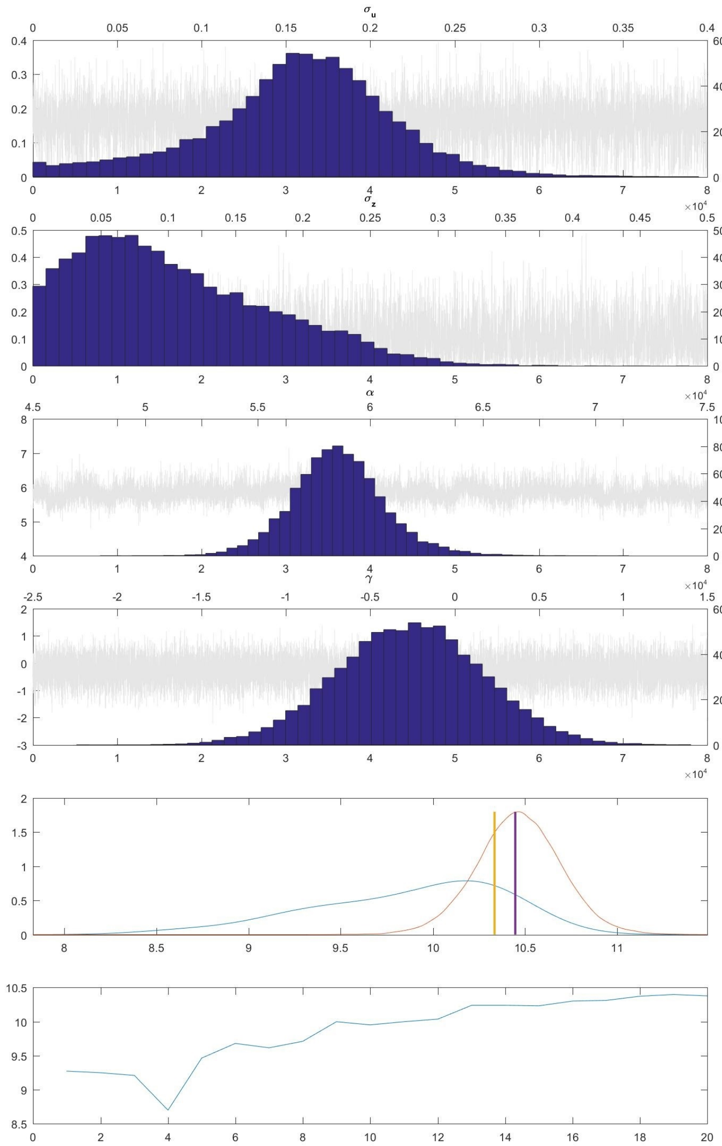

Fig. 3 Estimation Results for a Representative Accountant. This figure provides histograms (blue) and the trajectory of the corresponding Markov Chain (light grey) of the individual parameters σ_i^u,σ_i^z, α_i and γ_i in the first four plots. In plot five, the naive density estimate for the historic income trajectory (blue), the density forecast based on the income model (red), and the calculated price intervals are given. Thereby the yellow (purple) vertical bar represents the lower (upper) bound. The bottom plot depicts the historic income trajectory of the individual.

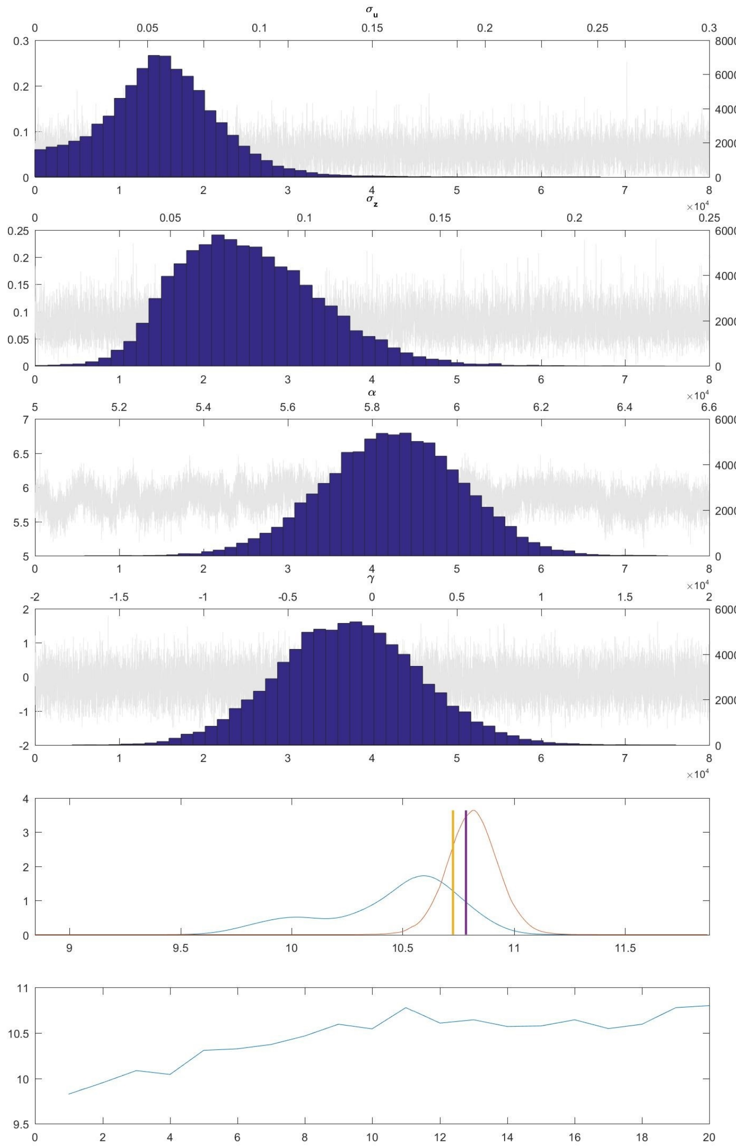

Fig. 4 Estimation Results for a Representative Mathematician. This figure provides histograms (blue) and the trajectory of the corresponding Markov Chain (light grey) of the individual parameters σ_i^u,σ_i^z, α_i and γ_i in the first four plots. In plot five, the naive density estimate for the historic income trajectory (blue), the density forecast based on the income model (red), and the calculated price intervals are given. Thereby the yellow (purple) vertical bar represents the lower (upper) bound. The bottom plot depicts the historic income trajectory of the individual.

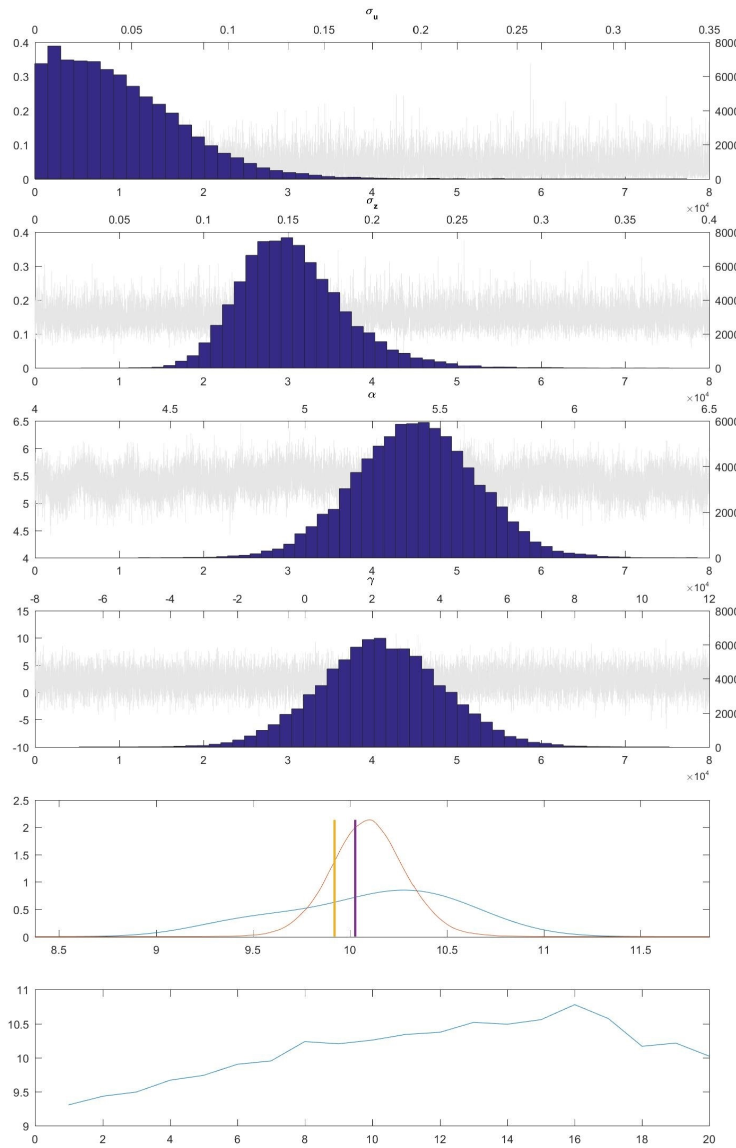

Fig. 5 Estimation Results for a Representative Author. This figure provides histograms (blue) and the trajectory of the corresponding Markov Chain (light grey) of the individual parameters σ_i^u,σ_i^z, α_i and γ_i in the first four plots. In plot five, the naive density estimate for the historic income trajectory (blue), the density forecast based on the income model (red), and the calculated price intervals are given. Thereby the yellow (purple) vertical bar represents the lower (upper) bound. The bottom plot depicts the historic income trajectory of the individual.