Schmollers Jahrbuch 123 (2003), 3 – 14
Duncker & Humblot, Berlin

Gender Differences in German Upward Income Mobility

By Ira N. Gang, John Landon-Lane and Myeong-Su Yun*

Abstract

We examine the upward labor income mobility of men and women in Germany using the GSOEP Cross National Equivalent File. Women have greater overall income mobility. However, utilizing a measure of upward income mobility and calculating the posterior probability that men's upward income mobility is greater than women's, we find that men have overall greater upward income mobility. Women have greater upward mobility in the lower initial income classes, while in the upper initial income brackets men's mobility is higher than women's.

JEL Classification: D 3, D 63, J 7

1. Introduction

In this paper we explore the upward income mobility of men and women in Germany over the period 1984 to 1997. In terms of labor income mobility, we examine whether men and women have approximately the same degree of upward mobility across the income distribution and whether upward income mobility varies by gender among the lower, middle and upper parts of the distribution.

We examine the labor income mobility of men and women in Germany using the GSOEP Cross National Equivalent File. We examine the dynamics of the income distribution – the movement of women and men through the distribution of income over time. We model the dynamics of the income distribution as a first order Markov chain. Bayesian methods are used to characterize the distribution of all the functions of the transition probability matrix. In particular, we are able to estimate the probabilities of an individual moving from one income classification to another, formally compare and contrast var-

* An earlier version of this paper was presented at the 5th International German Socio-Economic Panel User Conference, July 3 – 4, 2002, Berlin, Germany.

ious mobility indices across different subsamples of the data, and formally compare and test various hypotheses on the convergence properties of the income distribution. We are most interested in utilizing measures of upward income mobility and testing different hypotheses on the transitional dynamics of the income distribution.

2. Measuring Upward Income Mobility

In this paper we apply the results from Gang, Landon-Lane and Yun (2002b) to data from Germany. What follows is a brief discussion of the model and the estimation strategy. We model the dynamics of labor income using a first order Markov chain. The use of Markov-chain models to study income dynamics has a long history with notable contributions by Champernowne (1953) and Shorrocks (1976).

Suppose that there are a finite number, C, of income classes and let π represent the income distribution over these C income classes. The first order Markov assumption then assumes that

$$P(\pi_t|\pi_{t-1}, \pi_{t-2} \ldots, \pi_{t-j}) = P(\pi_t|\pi_{t-1}) \ \forall\, j = 2, 3, \ldots, \tag{1}$$

where $P(.)$ represents the conditional probability distribution of π.

Let the probability of transiting from class i in period $t-1$ $(\pi_{t-1} = i)$ to class j in period t $(\pi_t = j)$ is $P(\pi_t = j|\pi_{t-1} = i) \equiv p_{ij}$, so that the Markov transition matrix, **P,** can be defined as $\mathbf{P} = [p_{ij}]$. Hence the income distribution at period t can be represented as

$$\pi_t^{'} = \pi_0^{'}\mathbf{P}^t \ , \tag{2}$$

where where π_0 is the initial income distribution. For any initial distribution, π_0, the limit of the process described in (2) is unique if there is only one eigenvalue of $\mathbf{P}$ with modulus 1.[1] The limiting or invariant distribution, π, satisfies

$$\bar{\pi}^{'} = \bar{\pi}^{'}\mathbf{P} \ . \tag{3}$$

Using the Markov assumption there are many measures of overall income mobility that one may define (Shorrocks (1978) and Geweke, Marshall and Zarkin (1986)). A measure of overall income mobility measure that is commonly reported in the literature is the measure due to Shorrocks (1978), which is defined as

[1] Implicitly we are assuming that the eigenvalues have been ordered from highest to lowest in terms of magnitude. As **P** is row stochastic we know that the highest eigenvalue, in terms of magnitude, is 1. If the magnitude of the second eigenvalue is strictly less than 1 then we know that the invariant distribution is unique.

(4) $$\mathcal{M}_s(P) = \frac{C - tr(\mathbf{P})}{C - 1} \ .$$

The Shorrocks measure can be shown to be the inverse of the harmonic mean of the expected length of stay in an income class, scaled by a factor of $C = (C - 1)$. This index satisfies the monotonicity, immobility and strong immobility persistence criteria and hence is internally consistent.[2]

In Gang, Landon-Lane, and Yun (2002b), we show how this measure can be decomposed into its upward and downward income mobility components. We also show that these upward and downward income mobility indices are internally consistent with respect to the persistence criteria noted above. The measure of upward mobility that we use is

(5) $$\overline{\mathcal{M}}_{U|i}(\mathbf{P}) = \frac{1}{C-1}\sum_{k=1}^{C-1}\mathcal{M}_{U|k}(\mathbf{P}) \ ,$$

where

(6) $$\overline{\mathcal{M}}_{U|i}(\mathbf{P}) = \sum_{k=i+1}^{C} p_{ik} \ .$$

Here, $\mathcal{M}_{U|i}$ measures the conditional probability of moving up from income class i to an income class above i, and $\mathcal{M}_{U|i}$ is the average conditional probability of moving to a higher income class. These measures allow us to characterize any differences between males and females in terms of ability of moving to a higher income class.

3. Data and Prior Distribution

3.1 Data

We need panel data in order to study gender differences in upward mobility in labor income. We use samples drawn from the Cross National Equivalent File (CNEF) of the German Socio-Economic Panel (GSOEP).[3] The GSOEP contains information regarding not only demographic characteristics but also

2 See Geweke, Marshall, and Zarkin (1986) for a complete discussion on the properties of these mobility indices.

3 The GSOEP-CNEF are available thanks to efforts of researchers and staff at Cornell University and the German Institute for Economic Research (DIW). For details of making equivalent files across countries, see the homepage of this project, http://www.human.cornell. edu/pam / gsoep/equivfil.cfm.

labor market activities including labor income. Our variable of interest is real labor income which we calculate using data from the CNEF.[4]

We use the West German sample from the GSOEP (sample A). We exclude the over- sample containing the main immigrant groups to concentrate on income mobility among those whose entire life experience and education took place in Germany. We also exclude those who work in agriculture. In order to study only workers who have a strong attachment to the labor market, we restrict the sample to those who work in full-time jobs in both starting and ending years, 1984 and 1997.[5] Full-time workers are those who work 35 hours or more per week on average. We study only workers not younger than 25 years in the beginning year and not older than 60 years in the ending year of the period. Hence, we select people from age 25 to 47 in 1984.

One benefit of defining the transition period to be thirteen years is that there is enough time to allow workers to progress in their chosen careers, hence allowing for the greatest chance of a transition out of their initial income class. However, defining such a large transition period comes at a price of reducing the number of individuals that we observe.

Table 1 shows mean labor income by gender for 1984 and 1997. In addition to the means for our sample, Table 1 also shows the incomes of all workers (including part-time) and full time workers appearing only in 1984 or 1987. The sample we are using, “careerworkers”, i.e., those who are full time workers both in the beginning and ending periods, have the highest incomes. In this sample, men in 1984 enjoy an annual labor income premium of 46.71 percent over women. For 1997 this premium is 31.38 percent.

3.2 Prior Distributions

This paper uses Bayesian methods to estimate and make inferences from the Markov chain model outlined in section 2. One important consequence of using Bayesian methods is that it is simple to characterize the distribution of any function of the primal parameters, π_0 and $\mathbf{P}$, of the model and any, possibly non-linear, function of these primal parameters. In this paper, the functions

---

4 We compute labor income using the consumer price index (base year: 1991) and converting German Marks to US dollars using a purchasing power parity exchange rate (PPP) in 1991. The PPP in 1991 is 2.09 DM per one US dollar, while the exchange rate in the same year is 1.66 DM per a dollar. Also note that we rescaled German CPI by moving the base year to 1991 from 1999. This was done in preparation for other comparative work in which we are engaged. See Gang, Landon-Lane and Yun (2002a).

5 We choose people who were full-time job workers in both year 1984 and 1997 and study the 13 year transition. The fact that they worked in full-time jobs in both years does not necessarily mean that they worked in a full-time job throughout the period.

Table 1

Mean Income Level (constant US$, base year = 1991)

	Germany			
	1984		1997	
	Male	Female	Male	Female
	Full-time workers in both years			
Mean	26553	18099	32377	24644
std. dev.	(23694)	(8214)	(16569)	(10051)
sample size	643	132	643	132
	Full-time workers in respective year			
Mean	25507	17028	32618	22952
std. dev.	(21857)	(12012)	(16565)	(12396)
sample size	1480	503	748	241
	Workers in respective year			
Mean	24276	12198	31363	15716
std. dev.	(21450)	(10367)	(16546)	(11891)
sample size	1657	1035	824	566

Note1: Workers are restricted to working in non-agriculture and aged 25 to 47 years old in 1984.
Note2: German Mark is converted to U.S. dollar using PPP in 1991 (2.09DM / US$)

of the primal parameters that we are interested in are the various mobility measures described above.

As we use a Bayesian estimation strategy, we need to construct priors for the unknown parameters of our model. The unknown parameters of the first order Markov chain model are π_0 and **P**. We propose conjugate Dirichlet priors for π_0 and **P** parameterized by the vector a_0 and the matrix **A** respectively. These priors have a notional data interpretation in that $a_{0i} - 1$ can be interpreted as the number of individuals initially contained in income class i, while $A_{ij} - 1$ can be interpreted as the number of individuals transiting from income class i to income class j in the notional prior data set.

We take a neutral stance with our priors in that we want the data to tell the story. Noting that the prior has a notional data interpretation, we propose priors that are generated from a notional data set that is one tenth the size of the observed sample. For example, if the sample that we are using contains one thousand individuals then the prior would be parameterized so that it could be interpreted as coming from a notional sample of 100 individuals.

The prior distributions for all data sets used in this paper are scalar multiples of the following prior distributions. Table 2 contains the values for a_0 while Table 3 contains the values for A assuming a notional sample size of 100. We define ten income classes that are equal in log length.

Table 2

Initial Distribution Prior: a_0

Income Class	1	2	3	4	5	6	7	8	9	10
a_{0i}	11	11	11	11	11	11	11	11	11	11

Table 3

Transition Matrix Prior: A

Income Class	1	2	3	4	5	6	7	8	9	10
A_{1j}	6.21	3.60	2.30	1.65	1.13	1.06	1.01	1.01	1.01	1.01
A_{2j}	3.06	5.13	3.06	2.03	1.51	1.10	1.05	1.01	1.01	1.01
A_{3j}	1.93	2.87	4.75	2.87	1.93	1.46	1.09	1.04	1.01	1.01
A_{4j}	1.44	1.89	2.79	4.58	2.79	1.89	1.44	1.08	1.04	1.01
A_{5j}	1.08	1.44	1.88	2.77	4.55	2.77	1.88	1.44	1.08	1.04
A_{6j}	1.04	1.08	1.44	1.88	2.77	4.55	2.77	1.88	1.44	1.08
A_{7j}	1.01	1.04	1.08	1.44	1.89	2.79	4.58	2.79	1.89	1.44
A_{8j}	1.01	1.01	1.04	1.09	1.46	1.93	2.87	4.75	2.87	1.93
A_{9j}	1.01	1.01	1.01	1.05	1.10	1.51	2.03	3.06	5.13	3.06
A_{10j}	1.01	1.01	1.01	1.01	1.06	1.13	1.65	2.30	3.60	6.21

We place a flat prior over the parameters of the initial distribution. That is, we assume that all individuals have an equal chance of initially being in any income class. The prior for **P** has the characteristic, in order to be consistent with a_0, that there are ten individuals initially in each income class. The matrix **A** is then designed so that the highest prior probability is given to an individual staying in the same income class that she started in with decreasing probability given to moves further away from the starting income class. This prior is symmetric in the sense that the decline in the prior transition probability is not dependent on whether the move was to a lower or higher income class. This prior is neutral in the sense that there is equal prior probability assigned to all individuals of attaining any income class in the invariant distribution.

4. Results

We report a Shorrocks measure of overall income mobility, $\mathcal{M}_s(\mathbf{P})$ (see (1)), which is an average, across all income classes, of the conditional probabilities of an individual moving out of their current income class. This measure is a measure of upward and downward mobility combined. We also report our measure of upward mobility, $\mathcal{M}_{U|i}$. We report both measures for the full sample and we report $\mathcal{M}_{U|i}$ for low, middle and high sub-groups of the income classes.

Following Champernowne (1953), real incomes for Germany were divided up into ten income classes. The first and tenth income classes contain the bottom five percent and top five percent of the income distribution respectively. The other thresholds divide the intervening distribution into income ranges equal in log length.

The income class definitions are given in Table 4 below, as are the low, middle and high income subgroups. A number of different models were estimated. When modelling income mobility there is always uncertainty over the appropriate definition of the transition period.

Table 4

Income Class Definitions: 1991 US$

Income Class	Income Range	Sub-Group
1	[0, 10000)	Low
2	[10000, 12375)	Low
3	[12375, 15314)	Low
4	[15314, 18951)	Middle
5	[18951, 23452)	Middle
6	[23452, 29022)	Middle
7	[29022, 35915)	High
8	[35915, 44444)	High
9	[44444, 55000)	High
10	[55000, ∞)	High

The posterior means and standard deviations for π_0, $\mathbf{P}$, and $\bar{\pi}$ for males and females are presented in Appendix tables A.1 and A.2. Males in Germany have an initial income distribution that has more weight in the upper five income classes than the corresponding initial distribution for females. Moreover, the estimated transitions matrices are such that the invariant distributions for males, also have more mass in the upper income classes than the corresponding invariant distributions for females.

The mobility measures are presented in Table 5.

We see that females in Germany have greater income mobility overall. The posterior probability that the value of $\mathcal{M}_s(\mathbf{P})$ for males is higher than the

Table 5

Mobility Measures for 13 year transition 1984 – 1997

Mobility Measure	Group	Male	Female	Prob[Male > Female]
$\mathcal{M}_s(\mathbf{P})$	All	0.918	0.940 (0.019)	0.250 (0.028)
$\mathcal{M}_{U\|i}$	All	0.655	0.584 (0.021)	0.974 (0.029)
$\mathcal{M}_{U\|i}$	Low	0.771	0.812 (0.045)	0.253 (0.042)
$\mathcal{M}_{U\|i}$	Middle	0.722	0.703 (0.021)	0.641 (0.044)
$\mathcal{M}_{U\|i}$	High	0.473	0.236 (0.038)	0.998 (0.064)

corresponding values for females is 0.250. This implies that females have more overall mobility than males. However, when we look at the conditional probability measures, a different story emerges. First, males in Germany have an higher average conditional probability of moving up to a higher income class, 0.655 for men, 0.584 for women, the posterior probability being 0.974. When broken down over subclasses, we see that females have higher upward mobility in the lowest income group, Low, whereas males and females have similar upward income mobility in the middle income group, Middle. However, in the highest income group we see males totally dominating females in terms of the conditional probability of moving to a higher income class.

In order to check the robustness of the results to the definition of the transition pe- riod, we also estimate a Markov chain with a five year transition using data from the beginning, middle and end of the sample. For the five year transitions we use full-time non-agricultural workers between the ages of 25 and 55 in the initial year of the transition. Qualitatively, all of our results are robust to the choice of transition period.

5. Conclusion

In this paper we examine the dynamics of Germany's income distribution of Germany as a finite state first order Markov chain. We estimated this model using Bayesian methods with a neutral prior that was designed to reflect relative uncertainty on the part of the researcher. Once the model was estimated, we then were able to analyze the income mobility properties of the data. In particular, we analyzed the upward income mobility characteristics of the data separately for males and females.

We studied where women and men are located in the labor income distribution and the change in this position over time. Our study of the labor income mobility of men and women in Germany employed the Cross National Equivalent File, drawn from the German Socio-Economic Panel.

Overall, while females in Germany enjoy greater overall income mobility, we find that males have a significantly higher upward income mobility for the higher initial income classes. Females' upward income mobility measures compare favorably with males in the lower income classes, with mixed results in the middle income classes.

References

Champernowne, D. G. (1953), A Model of Income Distribution, in: Economic Journal 63, 318 – 351.

Gang, I. N. / *Landon-Lane,* J. S. / *Yun,* M.-S. (2002a), Does the Glass Ceiling Exist?: A Cross-National Perspective on Gender Income Mobility, mimeo.

– (2002b), Decomposing Income Mobility: Theory and Applications, mimeo.

Geweke, J. F. / *Marshall,* C. / *Zarkin,* G. A. (1986), Mobility Indices in Continuous Time Markov Chains, in: Econometrica 54, 1407 – 1423.

Shorrocks, A. F. (1976), Income Mobility and the Markov Assumption, in: Economic Journal 86, 566 – 578.

– (1978), The Measurement of Mobility, in: Econometrica 46, 1013 – 1024.

A. Posterior Estimates for German Data

Table A.1

Posterior Estimates: GERMAN Males (1984 – 1997)

Initial Distribution: π_0									
0.023	0.022	0.070	0.201	0.233	0.197	0.130	0.055	0.031	0.038
(0.006)	(0.006)	(0.009)	(0.015)	(0.016)	(0.015)	(0.012)	(0.009)	(0.007)	(0.007)
Transition Matrix: **P**									
0.172	0.106	0.072	0.136	0.080	0.161	0.077	0.078	0.040	0.079
(0.075)	(0.059)	(0.052)	(0.068)	(0.052)	(0.071)	(0.050)	(0.051)	(0.039)	(0.049)
0.176	0.150	0.094	0.110	0.139	0.087	0.042	0.121	0.042	0.040
(0.077)	(0.072)	(0.060)	(0.062)	(0.071)	(0.056)	(0.040)	(0.063)	(0.040)	(0.040)
0.061	0.053	0.073	0.207	0.260	0.141	0.103	0.051	0.033	0.018
(0.031)	(0.029)	(0.033)	(0.052)	(0.057)	(0.044)	(0.040)	(0.029)	(0.023)	(0.017)
0.021	0.023	0.027	0.137	0.271	0.323	0.140	0.039	0.013	0.007
(0.011)	(0.011)	(0.013)	(0.027)	(0.035)	(0.039)	(0.028)	(0.016)	(0.010)	(0.007)
0.012	0.013	0.020	0.080	0.174	0.372	0.225	0.047	0.045	0.011
(0.008)	(0.009)	(0.010)	(0.020)	(0.029)	(0.036)	(0.030)	(0.016)	(0.016)	(0.008)
0.014	0.013	0.015	0.023	0.082	0.180	0.367	0.211	0.068	0.028
(0.010)	(0.010)	(0.010)	(0.012)	(0.022)	(0.031)	(0.039)	(0.033)	(0.020)	(0.013)
0.010	0.010	0.031	0.013	0.034	0.089	0.130	0.342	0.203	0.138
(0.010)	(0.010)	(0.017)	(0.011)	(0.018)	(0.027)	(0.034)	(0.047)	(0.040)	(0.035)
0.020	0.043	0.021	0.023	0.070	0.076	0.106	0.173	0.229	0.240
(0.020)	(0.029)	(0.019)	(0.023)	(0.038)	(0.037)	(0.041)	(0.054)	(0.061)	(0.058)
0.032	0.032	0.062	0.034	0.034	0.042	0.117	0.171	0.212	0.265
(0.030)	(0.031)	(0.040)	(0.032)	(0.030)	(0.034)	(0.057)	(0.066)	(0.070)	(0.077)
0.029	0.055	0.028	0.026	0.113	0.059	0.147	0.078	0.127	0.340
(0.027)	(0.037)	(0.027)	(0.026)	(0.050)	(0.038)	(0.058)	(0.044)	(0.054)	(0.077)
Invariant Distribution: $\bar{\pi}$									
0.032	0.037	0.035	0.047	0.096	0.129	0.161	0.162	0.138	0.164
(0.010)	(0.011)	(0.009)	(0.010)	(0.014)	(0.015)	(0.016)	(0.019)	(0.021)	(0.027)
Sample Size									
643									

Table A.2

Posterior Estimates: GERMAN Females (1984 – 1997)

Initial Distribution: π_0									
0.093	0.087	0.197	0.202	0.206	0.124	0.028	0.021	0.022	0.022
(0.023)	(0.022)	(0.032)	(0.033)	(0.031)	(0.027)	(0.013)	(0.012)	(0.012)	(0.012)
Transition Matrix: **P**									
0.198	0.146	0.224	0.133	0.043	0.040	0.045	0.087	0.043	0.041
(0.081)	(0.073)	(0.084)	(0.071)	(0.041)	(0.040)	(0.042)	(0.058)	(0.043)	(0.040)
0.102	0.069	0.188	0.323	0.048	0.089	0.046	0.046	0.045	0.043
(0.061)	(0.053)	(0.082)	(0.095)	(0.044)	(0.059)	(0.042)	(0.045)	(0.043)	(0.042)
0.028	0.032	0.135	0.266	0.283	0.103	0.051	0.050	0.025	0.026
(0.027)	(0.028)	(0.053)	(0.070)	(0.070)	(0.047)	(0.036)	(0.034)	(0.023)	(0.025)
0.026	0.028	0.032	0.136	0.354	0.223	0.099	0.051	0.025	0.025
(0.025)	(0.026)	(0.027)	(0.052)	(0.075)	(0.065)	(0.047)	(0.036)	(0.026)	(0.024)
0.049	0.025	0.027	0.030	0.156	0.248	0.320	0.075	0.023	0.049
(0.035)	(0.023)	(0.026)	(0.026)	(0.056)	(0.069)	(0.070)	(0.041)	(0.022)	(0.033)
0.034	0.036	0.037	0.039	0.043	0.194	0.395	0.110	0.073	0.038
(0.032)	(0.034)	(0.035)	(0.036)	(0.037)	(0.071)	(0.088)	(0.058)	(0.048)	(0.037)
0.073	0.070	0.081	0.075	0.085	0.096	0.188	0.168	0.083	0.081
(0.070)	(0.065)	(0.073)	(0.067)	(0.075)	(0.081)	(0.104)	(0.098)	(0.070)	(0.072)
0.081	0.082	0.077	0.083	0.090	0.093	0.107	0.199	0.100	0.089
(0.073)	(0.075)	(0.073)	(0.075)	(0.077)	(0.078)	(0.082)	(0.110)	(0.080)	(0.078)
0.082	0.080	0.079	0.079	0.085	0.089	0.093	0.103	0.122	0.188
(0.076)	(0.076)	(0.073)	(0.074)	(0.074)	(0.080)	(0.085)	(0.088)	(0.090)	(0.106)
0.082	0.081	0.079	0.080	0.082	0.080	0.085	0.177	0.108	0.146
(0.076)	(0.073)	(0.071)	(0.074)	(0.074)	(0.076)	(0.074)	(0.105)	(0.085)	(0.101)
Invariant Distribution: $\bar{\pi}$									
0.068	0.059	0.082	0.106	0.128	0.137	0.174	0.114	0.064	0.068
(0.022)	(0.018)	(0.020)	(0.021)	(0.024)	(0.027)	(0.031)	(0.029)	(0.021)	(0.023)
Sample Size									
132									