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Statistical Matching of Administrative and Survey Data: An Application to Wealth Inequality Analysis

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Abstract

Using population representative survey data from the German Socio-Economic Panel (SOEP) and administrative pension records from the Statutory Pension Insurance, the authors compare four statistical matching techniques to complement survey information on net worth with social security wealth (SSW) information from the administrative records. The unique properties of the linked data allow for a straight control of the quality of matches under each technique. Based on various evaluation criteria, *Mahalanobis distance matching* performs best. Exploiting the advantages of the newly assembled data, the authors include SSW in a wealth inequality analysis. Despite its quantitative relevance, SSW is thus far omitted from such analyses because adequate micro data are lacking. The inclusion of SSW doubles the level of net worth and decreases inequality by almost 25 percent. Moreover, the results reveal striking differences along occupational lines.

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Introduction

Since the early 1980s, the popularity of statistical matching has steadily increased, not just in sociology and economics (Heckman, Ichimura, and Todd 1997; Rosenbaum and Rubin 1983) but also in other disciplines (Baiocchi et al. 2010). In the social sciences, studies based on statistical matching typically evaluate the efficacy of government policies and programs (Dehejia and Wahba 1999). In these applications, researchers face the fundamental problem of not knowing how a treated individual (e.g., a person who participated in a certain program) would have fared if he or she had not received the treatment (Arceneaux, Gerber, and Green 2010; Morgan and Harding 2006). Statistical matching helps overcome this constraint by comparing the difference in outcomes between individuals who share a set of common background characteristics and who either do or do not receive a certain treatment (Rosenbaum and Rubin 1983).

Statistical matching also comes into play when required data are not available in one, but several data sets that cannot be linked over a unique identifier (Kadane [1978] 2001; Moriarity and Scheuren 2001; Rodgers 1984).[1] This problem occurs if mounting a new survey is too costly or if survey respondents are unable to provide reliable information. In these situations, statistical matching links records from one data set with needed information from the second source (Rubin 1986). The linked information is not from the *same individuals*, but rather from observations with identical (or almost identical) background attributes in both data sets (Elliott and Davis 2005).

This article applies statistical matching for the purpose of data fusion and not for the estimation of causal effects in a treatment/control group setting. Given there is no unambiguous theoretical foundation on how to complement one data set with information from another, this article compares four variants of statistical matching in order to identify the best technique for the data at hand (Little 1988; Rässler 2002). The objective is to complement survey data on net worth from the population representative German Socio-Economic Panel (SOEP) with information on social security wealth (SSW) from the Sample of Active Pension Accounts (SAPA), an administrative data set maintained by the *Deutsche Rentenversicherung*, the German Statutory Pension Insurance.[2] The unique properties of the matched data provide an effective control for the quality of matches under each statistical matching strategy, thus allowing the authors to assess which technique fares best for the data at hand (Masterson 2010). An additional link to divorce statistics, as divorce affects pension rights for the individuals involved, thus controls for otherwise unconsidered effects that arise from a marital split.

The newly assembled data opens up countless research possibilities. We exploit the data and perform a wealth inequality analysis that includes SSW. Social security wealth is defined as the current sum of pension entitlements a person has accumulated in a given year—in this application, 2007. For retirees, SSW equals the monthly social security benefit, whereas for individuals who are still in the workforce, it is the current amount of entitlements stored in their social security earnings record.[3] So far, SSW is omitted from wealth analyses because of the lack of adequate micro data. While the SOEP collects extensive wealth data, information on SSW is difficult to obtain because respondents typically do not know their current pension entitlements, unless they are already retired and receiving a monthly benefit payment.[4] In contrast, the Statutory Pension Insurance keeps data on SSW, but lacks information on standard wealth categories and covariates that are beyond the needs of the agency. Especially for comparative analyses, the omission of SSW from standard wealth estimates raises issues of comparability (Frick and Headey 2009). Including SSW helps us to draw a more precise picture of the distribution of wealth in Germany.

The remainder of this article is organized as follows: The second section sets out some background information on the system of old age provision in Germany and the concept of SSW. The third section describes the data and the fourth section presents the overall matching strategy. The fifth section contrasts four statistical matching techniques and compares their performance for the groups of retirees. The technique that serves our purpose best is then applied to the total population providing the basis for the extended wealth measure that includes SSW. The sixth section presents the results of the wealth inequality analyses and the final section closes with some concluding remarks.

The System of Old Age Provision in Germany

Distinctive institutional features account for differences in old age provision across occupational groups in Germany. The Statutory Pension Insurance covers the majority of the German resident population but systematically excludes certain groups, such as civil servants or the self-employed. To appreciate differences in coverage and the accumulation of SSW across occupational groups, this section briefly sketches the system of old age provision in Germany and highlights the consequences for the statistical matching exercise.[5]

The Statutory Pension Insurance is compulsory and by far the most important pillar in the provision of retirement benefits in Germany. Throughout their adult working lives, more than 90 percent of the population contributes at least once to the public pension scheme. Today, the scheme covers more than 35 million actively insured individuals and pays benefits to almost 25 million retirees (Deutsche Rentenversicherung 2010).[6] Benefits from the public pension scheme are still the predominant source of retirement income for this group (Kortmann and Halbherr 2008) with occupational and private pensions clearly playing a secondary role.[7] For employees, the accumulation of SSW usually starts with the first job that is subject to social insurance contributions and ends with the transition into retirement. In these type of jobs, employees pay contributions into the social security system, a certain fixed share of their earnings up to some maximum amount. The employer matches these payments.[8] By paying contributions into the system, employees accumulate SSW. Individuals can also accrue pension rights during certain periods of nonemployment, such as spells of education, unemployment, or sickness. And finally, divorce affects the individual's SSW as well. The Statutory Pension Insurance carries out a splitting of pension rights accrued by husband and wife during their marriage (see Second Match: "Record Linkage" of SAPA and Divorce Statistics subsection for further details).[9] Taking all these factors into account, SSW corresponds roughly to the individual's earnings history and retirement benefits are a proxy for a person's lifecycle labor market attachment.[10]

A separate, noncontributory, pension scheme covers the 1.8 million active civil servants and provides benefits to 680,000 former public sector employees and to 300,000 survivors (Bundesministerium für Arbeit and Soziales 2008). By definition, civil servants become part of the civil servants scheme from which they cannot, and have no reason to, opt out. Their SSW does not accumulate over the life cycle, but solely depends on the final salary before retirement and years of service. With its generosity, the German civil service pension scheme stands out in comparative perspective, mitigating any need for additional retirement income.[11] Typically, we do not observe civil servants in SAPA data. Exceptions are those individuals who were not civil servants from the beginning of their career. In this case, they have worked for several years and accumulated SSW within the statutory pension insurance program.

For the 4.5 million self-employed in Germany, the system of old age provision is most heterogeneous. In fact, about 25 percent are permanently insured by separate compulsory schemes, including farmers and those in the liberal professions, such as lawyers or medical doctors. However, there is unequal conditions in terms of coverage and the provision of benefits While benefit levels for farmers are comparatively low, those self-employed in the liberal professions enjoy replacement rates comparable to those of civil servants (Loose and Frommert 2009). The rest of the self-employed lack formal coverage: Some rely exclusively on voluntary private pension investments, whereas others accumulate entitlements in several different schemes. The heterogeneity also has repercussions for the accumulation of SSW. For self-employed in compulsory schemes, SSW accumulates over the entire life cycle. The growing number of self-employed, without employees, typically has alternating spells of self-and dependent employment, which therefore also accumulate SSW in the public pension scheme.

This brief glance at the system of social security in Germany illustrates the quantitative relevance of the public pension scheme for the majority of the active and retired population. Over the course of their working life, they pay a significant portion of their earnings into the system that cannot be invested in alternative forms of old age provision. But this review also shows pronounced differences across occupational lines. These differences require special diligence in the matching and imputation exercise.

Data

In this article, we want to complement a standard measure of net worth with information on SSW as of 2007. *Net worth* is defined as the sum of owner-occupied and other real estate holdings, financial assets, assets from life insurance policies and private pension schemes, building loan contracts, business assets, valuables, net of any outstanding mortgage, and consumer debt. The *extended wealth measure*, which the authors present in this article, adds SSW to this standard net worth measure in order to provide a more comprehensive analysis of wealth and inequality in Germany. For this purpose, the authors present a double-match involving three data sets.

The first match employs 26 waves of panel data from the population representative *German SOEP* and links it with the *SAPA*. The SOEP is a broad interdisciplinary household panel study that started in 1984 (Wagner, Frick, and Schupp 2007). It covers a representative sample of the total population living in private households in Germany. The most recent accessible data were collected in 2009 with about 11,000 households and 20,000 individuals interviewed. The micro data provide detailed information on individuals, households, and families, which enables researchers to monitor living conditions over time. The standard components are surveyed annually, while special topic modules are asked every few years. In 2007, a special wealth module collected detailed wealth data at the individual level (see Frick, Grabka, and Marcus 2007), except for information on SSW.

The SAPA is a one percent random sample of pension accounts, containing records for approximately 570,000 individuals, both actively insured and recently retired. These records are representative of all individuals holding a pension account.[12] SAPA contains demographic and detailed benefit information, including the individual's aggregated SSW as of 2007. The longitudinal files provide information on monthly earnings, unemployment spells, periods of child care and long-term care, and so on. Like SOEP data, SAPA provides individual information, but, however, SAPA does not collect household information.

The second match links data from the *Divorce Statistics Administering the Pension Rights Splitting between Divorcees* (henceforth, *Divorce Statistics*) maintained by the Statutory Pension Insurance to SAPA data. This second match solely serves the purpose of correcting for otherwise unconsidered effects (in the SOEP–SAPA match) that arise from a marital split. For this second match, the authors use record linkage.[13] The *Divorce Statistics* cover all divorce settlements—a total of 5.5 million cases—that involved a splitting of pension rights between ex-spouses since its introduction in 1977. Further, the scope of variables pertaining to the individual's marital history in divorce statistics go beyond those in SAPA, such as the month and year the marriage started and ended, but no information on the individual's current marital status. However, the information is only available for those individuals who experienced a divorce settlement. Hence, this sample population is different from the SOEP and SAPA sample populations.

First Match: Linking SOEP and SAPA

Notation and Conditional Independence

Irrespective of which variant of statistical matching we opt for in order to link SOEP and SAPA, we face the following initial situation. There are two sample files *A* (SOEP) and *B* (SAPA) that share a set of common variables and some variables unique to each data set. The background attributes observed in both data sets are referred to as *X* variables, $X = (X_1, \ldots, X_p)$. Variables unique to the SOEP will be referred to as *Y* variables, $Y = (Y_1, \ldots, Y_Q)$, whereas variables unique to SAPA will be referred to as *Z* variables, $Z = (Z_1, \ldots, Z_R)$. By means of statistical matching, we complement *Y* variables on net worth with the *Z* variable on SSW using the common *X* variables. The population representativeness of SOEP data dictates the matching direction: SOEP is the *recipient* and SAPA the *donor* file.[14]

We face an identification problem, because we do not observe net worth and SSW jointly and their covariance is unknown. For the results to be meaningful, the conditional independence assumption (CIA) has to hold, meaning that Y and Z variables are conditionally independent given the matching variables X (D'Orazio, Di Zio, and Scanu 2006; Rässler 2002).

Comparing Four Variants of Statistical Matching

In order to find the best statistical matching approach to complement information on net worth with SSW for the data at hand, this article compares four techniques. These techniques cover the range of available statistical matching routines going from relatively simple approaches such as the *random within cell hot deck imputation* to more refined techniques such as *Mahalanobis distance matching,* which takes the maximum of continuous X variables into account.

Random within cell hot deck imputation (henceforth, "hot deck") completes records with missing data points with values from statistically similar, but complete records (Andridge and Little 2010; Ford 1983). Typically, both records—complete and incomplete—are part of the same data set. In our application, SSW is missing for all SOEP, but available for all SAPA records, which corresponds to the setup for *cold deck* routines. In this article, we pretend that sample file A and B originate from the same data. Therefore, we apply hot deck imputation to replace missing values of SSW in SOEP data with observed values in SAPA. The imputation is carried out within predefined matching strata using a number of common categorical X variables.[15] Within these groups, missing values are imputed by random assignment.

Based on SAPA data, *regression imputation* estimates multivariate ordinary least squares (OLS) regression models within different imputation classes. In these models, the individual's SSW is a linear function of the X variables, the set of background attributes available in both data sets. Based on the estimates, the authors perform out-of-sample predictions of SSW, imputing the respective value for all SOEP observations. To mitigate the *regression to the mean effect* inherent in predictions, residuals are randomly assigned to the respective predictions to preserve the variance of the distribution (Copas 1997).

Strictly speaking, *predictive mean matching* (PMM) also belongs to the group of hot deck imputation routines. PMM differs from the above hot deck approach in that it combines parametric and nonparametric techniques to impute a single variable with missing values (SSW). In a first step, PMM makes use of a parametric model (OLS regression) that describes the individual's SSW as a function of all matching variables. In a second step, PMM selects from all fully observed units the nearest neighbor donor that has the smallest distance to each incomplete observation (Little 1988; Rubin 1986). Unlike regression imputation, PMM imputes actually occurring and not constructed values.

Mahalanobis distance matching (Mahalanobis 1936) is a procedure frequently used in *cluster analysis*. The procedure calculates a Mahalanobis distance d_{ij} comparing each observation i_A in the SOEP to each observation j_B in SAPA based on a vector of the common X variables. The *statistical donor* minimizes the distance d_{ij} between the SOEP respondent and the SAPA observation. Unlike the *Euclidean distance*, the Mahalanobis distance score incorporates both correlations between matching variables and differences in variances. First, this implies that highly correlated matching variables do not enter the computation of the Mahalanobis distance with the same weight. Further, the Mahalanobis distance controls for differences in variances of the considered matching variables. Later, we will show why this property is useful in this application.

For all techniques, the authors apply a single imputation instead of multiple imputation routine in order to augment the measure of net worth in SOEP data with information on SSW from SAPA data. The application of single imputation is sufficient, given that the following analysis of extended net worth does not aim at drawing inference.[16]

Matching Variables

The set of common X variables distinguishes categorical *slice* and continuous *matching* variables.[17] Slice variables partition the data to only match individuals within certain predefined strata. The partitioning avoids matches of individuals that are sufficiently dissimilar, especially if these groups are believed to differ in how they accumulate SSW. Matching variables determine the best imputation or matching partners in SOEP and SAPA. The statistical matching occurs within six imputation classes.[18] Both data sets are stratified by gender, region, and immigrant status, resulting in the following classes: West German men, West German women, East German men, East German women, male migrants, and female migrants.[19] As for continuous matching variables, annual income measures dominate the matching exercise. We use an aggregate income measure that summarizes all income that qualifies for the accumulation of pension rights prior to the transition into retirement (earnings, unemployment benefits, sickness allowances, etc.). These variables are highly relevant because in a pay-as-you-go pension scheme, they are the best predictors for the individual's SSW.[20]

The income measure enters the equation as a three-year moving average to smooth individual income histories (average annual income for the years

1983 to 1985, 1984 to 1986, 1985 to 1987 ... 2004 to 2006). For all 2007 SOEP respondents with incomplete income profiles, we impute missing information starting in 2006 and going backward to 1983 for West Germany and 1991 for East Germany. The backward imputation applies a single regression-based imputation routine with random residual assignment. This routine makes maximum use of all available longitudinal information since the respondent's first participation in the SOEP.[21] For reasons of comparability of SOEP and SAPA, earnings are cut at the effective maximum contribution ceiling for each year.[22] Differential treatment of earnings in the statutory pension insurance depending on whether a person is a regular employee, civil servant, or self-employed requires consideration in the imputation.

A woman's fertility history is an additional piece of information that enters the matching as it determines the number of childcare credits that a woman receives. Women receive one year of pension credits for all children born before 1992 and three years for all children born thereafter.[23] We include the total number of childcare credits each woman has in 2007. In addition, various duration variables enter the computation. These measures reflect the number of years spent in different activities such as employment, unemployment, education, compulsory military, or community service (only for men), as well as long-term care giving. Finally, the matching and imputation exercise includes the age of the respondent in 2007.

This article tests the performance of four techniques that make different use of the available matching information: The hot deck approach ignores the continuous matching variables and imputes randomly within the six strata, in contrast to the other three approaches that also take the continuous variables into account.[24]

Second Match: "Record Linkage" of SAPA and Divorce Statistics[25]

The special role divorce plays in the accumulation of SSW cannot be addressed in the first match of SOEP and SAPA. This shortcoming is due to the fact that when SOEP respondents report their monthly pension benefit, it is impossible for them to tell entitlements resulting from employment (or other individual pension relevant circumstances) and those resulting from the divorce settlement apart. Hence, the authors expect that the premium or deduction resulting out of the pension splitting between former husband and wife leads to a systematic bias in the linkage of SOEP and SAPA.

These potentially biased matching results motivate a second match of SAPA and Divorce Statistics using record linkage. Information available in the Divorce Statistics allow for the correction of the *divorce bias*. With

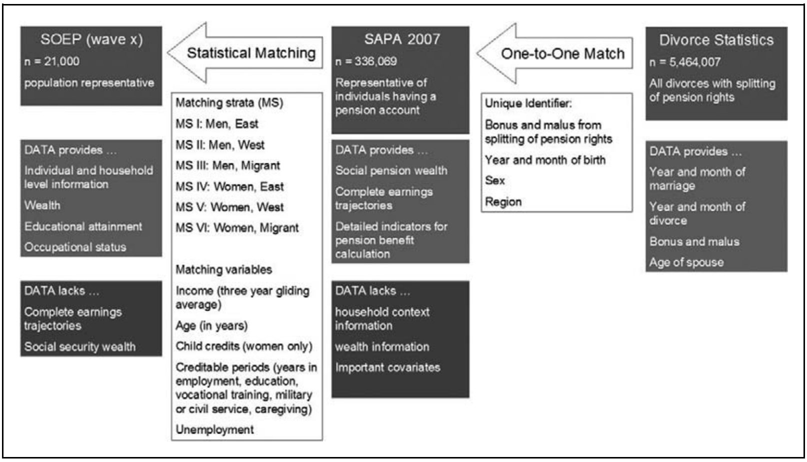

Figure 1. Statistical matching process—SOEP, VSKT and Divorce statistics.
Source: Authors' Illustration.

estimates from OLS regression models for each of the six matching classes, we correct for this bias in SOEP data. However, it is not feasible to correct the divorce bias by linking records of SOEP and *Divorce Statistics* due to the lack of uniquely identifying variables.[26] Moreover, information from the *Divorce Statistics* would not benefit the statistical matching of SOEP–SAPA, as it does not add any relevant information for the analyses on the distribution of wealth in Germany. Figure 1 summarizes the double-matching approach.

Assessing the Quality of Matches: Which Technique Performs Best?

Sample Specification and Evaluation Criteria

We test the performance of each matching technique based on the population of retirees. For this group, the data provide an effective benchmark to assess the quality of the matches. Retired SOEP respondents provide the presumably *true* monthly pension benefit (henceforth *observed benefit)* that allows for the comparison with the *simulated* benefit (henceforth, *matched benefit*) from each of the four matching techniques, respectively.[27]

We perform this test for recently retired individuals aged 60 to 67. To guarantee the consistency of both sample populations, the samples do not include disability pensioners because of significant differences in eligibility rules and pension benefit calculation as compared to old age pensioners. The analysis excludes civil servants because they lack pension-relevant income for most parts of their working life. If they accrued any entitlements in the public pension scheme, these are typically credited against their civil servants pension when they retire. For self-employed individuals in the SOEP, income information was set to zero for the years of self-employment because it is typically not pension-relevant. The samples consist of 659 SOEP and 34,353 SAPA observations.

We assess the validity of each approach using three criteria: (1) the correlation coefficient of the *observed* and *matched* public pension benefit; (2) the average differences between *observed* and *matched* benefit and the respective standard deviations; and (3) for the overall fit, a graphical representation (*kernel density plots*) of the individual differences between *observed* and *matched* benefit. Each criterion is evaluated for the total population and within each of the six matching strata.[28] The combination of criteria provides a good basis for the assessment of matching quality. Even though high correlation coefficients point toward a strong association, they do not tell whether the observed and matched pension benefits fall in the same range. Average differences between observed and matched benefits, as well as standard deviations, indicate whether the matching systematically assigns too high or too low values that result in a systematic bias. A kernel density plot is a good descriptive mean to check whether the distribution of individual differences is centered on zero, symmetric, and has a small variance.

Results

For the total population of retirees, pairwise correlations between *observed* and *matched* public pension benefits are best for Mahalanobis matching. The correlation coefficient r_{MAHA} of almost 0.7 is slightly higher than for PMM and the regression-based approach with 0.67 and 0.68, respectively. Hot deck imputation clearly lags behind ($r_{HOT} = 0.22$). The lack of association between observed and matched benefit for hot deck imputation is also true for the within-group correlations that range from -0.53 for female migrants to 0.17 for East German women. This result is due to the random assignment of matching partners without taking further continuous information into account.

For the other three techniques, within-group correlations always fall below the correlation coefficient of the total population except for the rather small group of female migrants ($r_{MAHA} = 0.82$, $r_{REG} = 0.79$, and $r_{PMM} = 0.76$). Concerning the other matching strata, PMM performs best for East

German men (r_{PMM} = 0.45) and male migrants (r_{PMM} = 0.63), the regression-based approach for East and West German women with 0.55 and 0.65, respectively. Mahalanobis fits best for female migrants ($r_{MAHA} = 0.82$) and West German men ($r_{MAHA} = 0.43$). Since the results are rather inconclusive with none of the techniques standing out, the correlation coefficient alone is not a sufficient criterion for the decision, which technique to apply.

The second evaluation criterion is the mean difference between observed and matched benefit:

$$\bar{d}_{i,j} = \frac{\text{SOEP}_{\text{SSW}_{\text{retired}}} - \text{SAPA}_{\text{SSW}_{\text{retired}}}}{n_{\text{retired}}}.$$

The difference describes how far off the matched benefit is from the observed public pension benefit. A small average distance and standard deviation are indicators for a good match. Considering the distance criterion for the total population, hot deck imputed values fare best when it comes to the average distance ($d_{HOT} = 16.4$), but poorly with respect to the standard deviation of 542.8. This standard deviation is significantly higher than for all the other techniques. Mahalanobis is second best in terms of distance and best with respect to the standard deviation ($d_{\text{MAHA}} = -74.8$; $SD = 320.6$). The regression-based approach and PMM are quite similar in their performance ($d_{\text{PMM}} = -101.6$; $SD = 327.5$ and $d_{\text{REG}} = 105.5$; $SD = 328.8$), but clearly lag behind Mahalanobis matching.

In Table 1, we rank the performance of techniques with respect to the within-group average distances and standard deviations between observed and matched benefit. The upper panel provides the average differences; the bottom panel displays the standard deviations. With respect to average differences between observed and matched benefit, Mahalanobis matching works best for West German men ($d_{\text{MAHA}} = -34.7$) and male migrants ($d_{\text{MAHA}} = -90.7$). Hot deck imputation performs best for East and West German women ($d_{\text{HOT}} = -53.6$; $d_{\text{HOT}} = 39.1$) and female migrants ($d_{\text{HOT}} = -110.4$), but clearly provides the worst results for men. PMM yields the best results for East German men ($d_{\text{PMM}} = -105.8$). Across all groups, Mahalanobis renders the best outcome with respect to the average distance criterion (average rank of 1.6).

Despite comparatively small average distances for groups 4 to 6 under hot deck, the standard deviation is by far the highest under hot deck across all groups. With respect to the standard deviation, PMM performs best for East German men as well as East and West German women, whereas Mahalanobis is better for West German men and male migrants. For female migrants, the distribution of matched values from the regression-based imputation and Mahalanobis has the lowest standard deviation. Overall, PMM and

Table 1. Average Distance and Standard Deviation Between Observed and Matched Benefit Across Matching Techniques.

		Men East (n = 126)	Men West (n = 138)	Men Migrant (n = 47)	Women East (n = 141)	Women West (n = 154)	Women Migrant (n = 28)	Avg. Rank
Hot Deck	Mean	−124	112	203	-54	39	91	
	$Rank_{Mean}$	4	4	4	1	1	1	2,5
Regression	Mean	−115	−43	−163	−126	−111	−142	
	$Rank_{Mean}$	3	2	3	4	3	3	3
PMM	Mean	−106	−70	−131	−91	−119	−145	
	$Rank_{Mean}$	1	3	2	3	4	4	2,8
Mahalanobis	Mean	−107	−35	−91	−70	−77	−110	
	$Rank_{Mean}$	2	1	1	2	2	2	1,6
Hot Deck	Std. Dev.	400	701	682	339	566	486	
	$Rank_{SD}$	4	4	4	4	4	4	4
Regression	Std. Dev.	291	387	409	298	315	218	
	$Rank_{SD}$	2	2	3	3	2	1	2,16
PMM	Std. Dev.	256	448	389	250	312	219	
	$Rank_{SD}$	1	3	2	1	1	3	1,83
Mahalanobis	Std. Dev.	316	376	382	260	317	218	
	$Rank_{SD}$	3	1	1	2	3	1	1,83

Source: SAPA (2007) and SOEP (2007); Authors' Calculations.

Mahalanobis fare best concerning the standard deviation, whereas hot deck performs worst, by far. With respect to both criteria, the within-group average differences between observed and matched benefits as well as the standard deviations, Mahalanobis is superior to any other technique.

Kernel density plots depict the distribution of differences between observed and matched benefit information for all four approaches. Ideally, these plots are symmetric, unimodal, and clustered around zero with a small standard deviation. Figure 2 presents the kernel density plots for the total population.

The graphic representation underlines that hot deck is not the appropriate imputation technique. The distribution of differences has a substantial standard deviation with very long tails on both sides. Despite its better performance relative to hot deck, the PMM distribution has no unambiguous peak. The distribution (dashed grey curve) appears to be much wider at the top with several smaller peaks. The kernel density plots for the regression approach (dotted curve) and Mahalanobis (solid curve) come closest to the ideal. The distribution for Mahalanobis is centered on zero but shows a small bump at +250 Euro. The kernel density curve for the regression-based technique has no such bump, but the peak of the distribution is more spread out.[29]

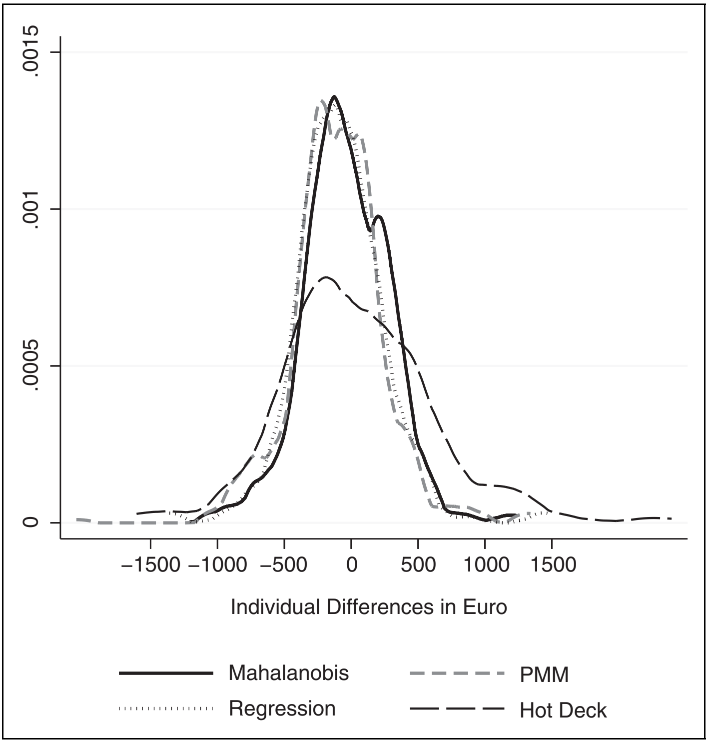

Figure 2. Kernel density plots for differences between observed and matched benefit information, total population.
Source: SAPA (2007) and SOEP (2007); Authors' Illustration.

Overall, the divorce correction improved the quality of matches. Table 2 presents the absolute average distances (using *Mahalanobis distance*) with and without the divorce correction for the divorced population only.[30]

Without the divorce correction, matched benefits were too large for divorced men and too small for divorced women.[31] The divorce correction shifts results in the expected direction. Consequently, the absolute average distance changed from $d_{W/O\ Correction} = -124.0$ to $d_{W.\ Correction} = -50.9$ for East German men and from $d_{W/O\ Correction} = -190.9$ to $d_{W.\ Correction} = 3.4$ for West German men, respectively.[32] In turn, differences for women shifted in the opposite direction. The absolute average distance for East German women is $d_{W/O\ Correction} = -8.5$ without and $d_{W.\ Correction} = -60.7$ with the correction. For West German women, the difference shifts from $d_{W/O\ Correction} = 117.5$ to $d_{W.\ Correction} = -58.4$. For almost

Table 2. Effect of the Divorce Correction—Only Divorcees.

Difference Between True and Simulated Pension Benefit (Euro)		With Divorce Correction	Without Divorce Correction	Absolute Effect
Total (n = 137)	Median	−63.2	−46.7	16.5
	M	−36.8	−38.3	−1.5
	SD	347.6	379.3	31.7
Men East (n = 26)	Median	−47.1	−92.0	−44.9
	M	−50.9	−124.0	−73.1
	SD	296.3	338.3	42.0
Men West (n = 33)	Median	77.9	−127.3	−205.2
	M	3.4	−190.9	−194.3
	SD	382.3	425.9	43.6
Women East (n = 25)	Median	−123.2	−63.9	59.3
	M	−60.7	−8.5	52.2
	SD	212.1	219.2	7.1
Women West (n = 42)	Median	−109.4	29.0	138.4
	M	−58.4	117.5	175.9
	SD	388.0	363.9	−24.1

Source: SAPA (2007) and SOEP (2007), Authors' Calculations.
Note: Migrants are omitted because of the small number of divorced migrants in the SOEP population.

all groups, the divorce correction reduces the standard deviation of differences between observed and matched benefit. Hence, the quality of matches for divorcees converges to the quality of nondivorced individuals.

The unique data situation allows for the test of conditional independence based on the population of retirees for which we perform the statistical matching and observe both variables: their net worth and social security benefit. First, we run two OLS models: Model I regresses the matching variables on the individual's social security benefit; Model II regresses the matching variables on total net worth. For the CIA to hold, the residuals derived from both predictions have to be uncorrelated. For the total population of retirees, we find a correlation of 0.057 with a t-statistic of 1.44. Therefore, we fail to reject the hypothesis that the correlation coefficient is significantly different from 0. Although it is impossible to test the assumption empirically, we assume this proposition to be true for the total population.[33]

Discussion

Mahalanobis distance matching performs best if we factor in all three criteria. Nonetheless, certain patterns require further explanation: First, a systematic negative bias in the average difference between observed and matched benefit. Second, significant between-group differences that point to better matches for some groups than for others.

The average distances are negative for the total population as well as for most of the individual groups, which indicates that the matched information is systematically higher than the reported benefit. The payment of insurance contributions for health and long-term care is one possible explanation for this bias. SAPA data provide the gross public pension benefit.[34] In turn, SOEP respondents likely report their public pension benefit *net* of health and long-term care premiums. Another explanation for the systematic bias is that the matching exercise fails to take actuarial adjustments for early retirement into account on the part of SAPA data, which possibly leads to an overestimation of approximated pension benefits.[35]

We find substantial differences in the quality of matches: On average, the quality is better for men than for women, better for West than for East Germans, and better for Germans than for migrants. Results of additional robustness tests indicate that the quality of matches is closely linked to the number of years a person has been observed in the SOEP as well as the number of years with income information larger zero.[36] Furthermore, the quality of the match depends on how good a predictor the observed information is for the individual's final public pension benefit, given that we do not observe the complete lifecycle of SOEP respondents.[37]

Matches are particularly good for West German men. For this group of SOEP respondents, we observe the annual income for more than half of their working life, which is a good predictor for their final public pension benefit.[38] In contrast, matches are less good for East German men. SOEP data collection in East Germany started only after German reunification. Therefore, the matching exercise dismisses almost two thirds of elderly East German men's working life that are relevant for their public pension benefit: First, this group has claims in special and additional pension schemes for former elites of the German Democratic Republic (GDR) that increase the final benefit significantly but cannot be controlled for in the data. Second, the labor markets East German men worked in and their earnings before reunification had nothing in common with the situation after the German reunification. In the centrally planned economy everybody had a job and unemployment was not an issue. This job security and the continuous working careers were favorable for the accumulation of SSW of East German men. However, post-reunification labor market experiences differed greatly with age-earnings profiles being flat and returns to tenure and experience significantly lower when compared to West German men (Orlowski and Riphahn 2009).[39]

Unemployment, for a significant share of this group even long-term unemployment largely limited the ability to accumulate SSW.[40] These reasons explain why the observation of only the most recent years might not be the best predictor for the final pension benefit of East German workers.

The quality of matches is better for East German women than for East German men. East German women benefit to a lesser extent from the transfer of entitlements from special and additional pension schemes than men. The biasing effects that these benefits have on the matching quality are therefore less strong for women.[41] Further, women in our sample were disadvantaged with respect to earnings and occupations before, but also lacked proper employment opportunities after reunification. The observed years of East German women's lives in the SOEP are to a greater extent *representative* for the unobserved years, which improves the matching quality.

The matching results for West German women appear to be less good than that for East German women. Despite a longer period of observation, data mostly cover the period of economic inactivity of these birth cohorts following the years of childbearing and childrearing. This inactivity is particularly prevalent among older birth cohorts of women as a consequence of the strong *female caretaker/male breadwinner notion* promoted in the West German postwar welfare state.[42] Due to these rather uniform working patterns, the years observed in the survey are not necessarily representative for the unobserved period of life. Therefore, the second half of West German women's working lives is not such a good predictor for their final public pension benefit. Following this line of argument, it comes as no surprise that the matching quality is poorer for migrants. On average, years observed for both male and female migrants fall short of those observed for natives. It is likely that these years are not representative for the total employment biography. Pensions based on bilateral social insurance treaties with other countries also account for large differences between observed and matched benefit information among migrants.[43] For the analysis, it is infeasible to separate benefits earned in Germany from benefits earned in other countries.

Based on the results, it is safe to apply Mahalanobis distance matching to the working age population to obtain the best estimate of SSW. The authors expect the matching quality to be even better for this segment of the population: First, the number of observations is significantly larger (14,247 SOEP with 288,655 SAPA observations); hence, SOEP observations have more potential matching partners to choose from. And second, the SOEP covers a greater share of peoples' working lives, which feeds more reliable information in the statistical matching and therefore reduces uncertainty.

Wealth Inequality

Determining the Present Value of Pension Entitlements

The inclusion of SSW in the wealth inequality analysis requires the calculation of the present value of pension entitlements (for a detailed description, see Rasner, Frick, and Grabka 2011). The present value considers pension rights from the statutory, company, and private pensions.[44] For retirees, we substitute the matched SSW with the *true* amount stated in the survey because this information seems to be more reliable than any simulated benefit could possibly be. For the working age employees, we keep the SSW as assigned by the Mahalanobis distance matching. The entitlements for active civil servants are approximated in the following way: As a final salary scheme, gross earnings during the last three years of service and the number of service years are the basis for the calculation of benefits.

The actual calculation of the present value of recurring pension payments requires information on life expectancy, retirement age, and the taxation of retirement income. As for the life expectancy, the authors rely on the 2005/2007 life tables of the German Federal Statistical Office. The life tables provide information on remaining life expectancy by sex and region (East and West Germany). Finally, differential taxation of retirement income, based on an individual's working occupation, is accounted for in the calculations.[45] For the calculation of the present value of such entitlements, differential 2007 tax rates apply depending on the occupational group. We assume the future indexation of pension payments to be in line with inflation, so that the real value of entitlements stays constant over time. For discounting purposes, we assume an interest rate of 2 percent.[46]

The Distribution of Total Individual Net Worth and SSW

The wealth inequality analysis compares a standard measure of net worth to an extended measure of net worth that includes SSW (henceforth, *extended wealth*) obtained from the statistical matching.

In a first step, we separate total net worth and SSW and take a look at their respective distributions. The first column of Table 3 indicates that the aggregate net worth for individuals in private households in Germany amounts to about 5.9 trillion Euro in 2007. If this amount was evenly split, each adult person would have about 83,000 Euro at his or her disposal. Comparing mean and median of the distribution of total net worth gives a first indication for the degree of overall inequality. In fact, median wealth equals 15,000 Euro. Thus, the mean exceeds the median by factor 5.5. With about 78,500 Euro, the

Table 3. Net Worth and Social Security Wealth in Germany[a], 2007.

	(1) Net Worth (in €)	(2) SSW[b] (in €)	(3) Extended Wealth (in €)	(4) Change (%) [(1)/(3)]
Sum in trillion Euro	5.908	5.581	11.489	94.5
Basic statistics				
Mean	83,077	78,479	161,556	94.5
Median	14,751	46,680	94,675	541.8
Wealth shares (%)				
Lowest quintile	−1.5	0.9	0.4	126.7
2nd q.	0.4	5.2	4.5	1025.0
3rd q.	3.9	12.0	11.8	202.6
4th q.	17.3	24.1	22.4	29.5
Highest quintile	79.9	57.7	60.9	−23.8
Population with zero or negative wealth (%)	28.1	4.5	3.3	−88.3
Inequality				
Gini coefficient	0.80	0.56	0.60	−24.6
HSCV	6.51	0.73	2.02	−68.9
P90:P50[c]	14.15	4.11	3.82	−72.9

Source: SAPA (2007) and SOEP (2007), Authors' Calculations.
Note: HSCV = half-squared coefficient of variation.
[a]Population: persons in private households aged 17 or older ($N = 69{,}321{,}834$).
[b]With a discount rate of 2 percent, without provision for dependants.
[c]Lowest value of the top 10 percent in the wealth distribution in relation to the median (50 percent).

average SSW comes close to average net worth (see column 2 in Table 3).[47] But, the distribution of SSW is less skewed than that of total net worth, because mean and median are closer. The mean exceeds the median by factor 1.7.

The evidence on the relationship between mean and median suggests significant differences in the distributions of net worth and SSW. The wealth shares provided in Table 3 further support this evidence. The top 20 percent of the adult population hold almost 80 percent of total net worth, whereas the three bottom quintiles own less than 3 percent of total net worth. About 28 percent of the adult population has no or even negative net worth, indicating that liabilities exceed gross wealth. In contrast less than 5 percent of the total population did not accumulate any SSW. Pension entitlements are by far more evenly distributed than net worth, mainly because almost everybody accumulates pension entitlements at least once over their working life. In addition, income is subject to contributions only to an upper limit in the Statutory Pension Insurance. Nevertheless, the highest quintile still holds the bulk of SSW with almost 58 percent of total SSW. The *Gini coefficient* reflects the differences in the distributions of these two wealth concepts. For net worth, the coefficient equals 0.8 indicating a high degree of inequality, whereas for SSW it amounts to 0.566.[48]

The inclusion of SSW in our extended wealth measure almost doubles the average net worth (161,500 Euro). However, a much stronger increase could be observed for the median, which reached nearly 95,000 Euro. Inequality is decreasing by one quarter for the Gini coefficient when moving from the standard to the extended measure of net worth. Those in the middle of the distribution profit the most with wealth shares mounting by almost eight percentage points.

Net worth and Extended Wealth across Occupational Groups

The individual's occupational status is a fundamental determinant not only for a person's income level and his or her ability to save but also an important proxy for the level of net worth.[49] Beyond that, the individual's occupational status is also relevant for the accumulation of SSW. The occupation determines the type of pension scheme a person belongs to and the rules by which SSW accumulates (compare to the section The System of Old Age Provision in Germany). Table 4 provides evidence on how occupational status relates to wealth holdings in Germany. It compares the three measures of interest: standard net worth, present value of SSW, and extended wealth. For a more complete picture, Table 4 gives information on the age/sex composition of each occupational group (median age and share of females) to better take compositional differences into account.

The results reveal substantial differences in wealth holdings across occupational groups. We also find that some occupational groups benefit to a greater extent from the inclusion of the present value of SSW than others. On average, net worth is highest for the self-employed, given that they must save more to private old age pension plans and because of their business capital itself, which makes a significant difference. Evidently, the more employees a self-employed person employs, the greater their total net worth. In contrast, unskilled, semiskilled workers and salaried employees (without vocational training) hold roughly 34,000 Euro in financial and material assets. In turn, skilled workers, such as foremen or masters, have nearly 70,000 Euro in assets, while employees with management responsibilities hold more than 120,000 Euro.

Table 4. Net Worth and Social Security Wealth by Selected Occupational Groups in Germany[a], 2007.

	Occupational Group	In Euro			Relative Change	Age in years	Share Female
		Net Worth	SSW[b]	Extended Wealth	In %	Median	In %
Workers and employees	Unskilled, semiskilled, salaried employees without an apprenticeship	33,618	53,965	87,582	161	43	55
	Trained and skilled, salaried employees in low qualification positions	46,964	56,043	103,007	119	42	41
	Foremen, masters, supervisors, salaried employees in qualified positions	69,256	60,128	129,384	87	42	58
	Salaried employees with extensive management responsibilities	122,778	74,955	197,734	61	42	33
Civil servants	Subclerical or clerical service class	67,019	92,135	159,154	137	40	36
	Executive or administrative class	145,775	149,484	295,259	103	47	41
Self-employed	Without any employees[c]	169,683	56,296	225,980	33	47	39
	With one to nine employees	351,185	38,064	389,249	11	46	25
	With ten or more employees	1,138,372	35,909	1,174,281	3	45	26
Not working	Persons of working age not gainfully employed	74,553	39,620	114,173	53	44	89
	Unemployed	15,406	52,070	67,476	338	42	53
Retired	Retirees in the public pension scheme	98,956	129,763	228,719	131	71	56
	Retirees in the civil servants pension scheme	187,510	313,436	500,946	167	69	220
	Total	83,077	78,479	161,556	94	48	50

Source: SAPA (2007) and SOEP (2007), Authors' Calculations.
[a]Population: persons in private households aged 17 or older ($N = 69{,}321{,}834$).
[b]With a discount rate of 2 percent, without provision for dependants.
[c]Including family members helping out.

In general, civil servants own above average net worth, which is especially true for civil servants in executive or administrative positions, with an average individual net worth of more than 140,000 Euro. Civil servants in the subclerical or clerical service accumulate substantially less (67,000 Euro), but still more than skilled workers and salaried employees.

In line with the standard lifecycle model of savings (Modigliani 1988), the elderly have above average net worth. This age effect is particularly striking for retired civil servants with a measure of net worth of nearly 190,000 Euro. In comparison, pensioners in the statutory public pension scheme have net worth of less than 100,000 Euro at their command. Civil servants are at an advantage in the accumulation of wealth not only because of the on average higher educational attainment but also because they do not have to pay contributions into their pension scheme, which allows for a higher saving rate.

The inclusion of the present value of SSW benefits civil servants most. Retired civil servants have more than 310,000 Euro SSW, while the respective figure for pensioners in the statutory public pension scheme not even reaches half of this amount (130,000 Euro). In the active population, it is also the group of civil servants who profit the most from the inclusion of SSW. For low- and medium-level civil servants, pension entitlements amount to 92,000 Euro. For high-level civil servants (executive and administrative class), these entitlements are even higher (almost 150,000 Euro). In fact, their SSW nearly doubles their net worth. Dependent employees do not benefit to the same extent from the inclusion of the present value of SSW. For the various groups of blue- and white-collar employees, SSW ranges from 54,000 Euro to 75,000 Euro. Currently unemployed have an average SSW of 52,000 Euro. This finding underlines the important role the public pension scheme plays in stabilizing the individual's economic position, even in case of (short term) unemployment. For the self-employed, the respective figures vary on a somewhat lower level compared to dependent employees (between 35,000 Euro and 56,000 Euro). Unlike other occupational groups, it is in the individual responsibility of the self-employed to provide for old age. They typically invest in life insurance policies or property. Following from this, the extended wealth measure clearly improves the position of civil servants relative to the self-employed.[50] Nonetheless, the self-employed stay on top of the wealth distribution.

Conclusion

This article compares four statistical matching techniques to complement data on wealth from a population representative survey with information on SSW from administrative pension records. Statistical matching proves to be a suitable technique to link information not available in one data set, but distributed across multiple data sets, which lack a common unique identifier. Rigorous robustness tests for the group of retirees identify Mahalanobis distance matching to be the best performing approach for the data at hand when compared to three alternative techniques.

Applying the statistical matching strategy to the total population allows for the calculation of the present value of pension entitlements. The results illustrate that SSW represents a considerable source of wealth worthwhile to consider in a wealth inequality analysis. Overall, SSW roughly amounts to 5.6 trillion Euro or—on average—78,500 Euro per adult. When combined with net worth, SSW almost doubles the measure of extended wealth with an average of more than 160,000 Euro. The extended measure of wealth reduces inequality (Gini coefficient) by one quarter compared to standard distributional analyses that only take financial and material assets into account. This marked reduction in inequality is mainly the result of the lesser spread in the distribution of SSW and due to the fact that almost every adult in Germany has at least some entitlements in the various old age pension schemes. We also find striking differences in levels of SSW across occupational groups. With respect to their position in the wealth hierarchy, civil servants benefit most from the consideration of pension wealth in the extended measure of wealth.

Future research in the area of statistical matching should test already available indicators (Rässler 2002; Rässler and Kiesl 2006) and aim at developing additional formal indicators to assess the matching quality. Ideally, these indicators should work even in the absence of an effective benchmark, such as the reported pension benefits of the group of retirees observed in the survey. In this application, Mahalanobis distance matching is the best matching technique, but it may not be in others. The comparison of four variants of statistical matching is appealing because it helps us better understand the compatibility of both data sets and which technique works best in which context. These robustness tests also come into play if we plan to complement one data set with more than just one variable from another data set.

Finally, establishing multiple statistical matching strategies might be one research direction worth following. Multiple statistical matching follows the idea of multiple imputation that has become the standard method to deal with missing data (Rubin 1987). The application of multiple matching procedures provide proper estimates of the variance that allow for research that goes beyond the descriptive analyses presented in this article. For drawing statistical inference from the matched SOEP–SAPA data, the elaboration of a chained equation approach or a multivariate normal imputation model (Schafer 1997) is certainly indispensable. Finally, multiple imputation routines could further enhance the relevance statistical matching has for research questions that require the combination of data from separate sources.

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Notes

1. So-called *record linkage* requires a unique identifier and the informed consent of survey respondents, because it links identical persons in two data sets. A 2009 pilot study tested the willingness of SHARE respondents in Germany to allow for record linkage using their Social Security Number (SSN). While 77 percent gave their consent, only 64 percent of those respondents provided their SSN. It is not yet verified whether the SSN provided is always correct. This outcome implies that less than 50 percent of respondents participating in the pilot study agreed to record linkage. There is good reason to believe that there are systematic differences between consenters and nonconsenters, which would add bias to the results. Another risk associated with record linkage lies in selective panel attrition in subsequent waves of the panel as a reaction of respondents to the record linkage efforts. For literature on consent patterns, see Jenkins et al. (2006).
2. Record linkage is infeasible for data confidentiality reasons. Moreover, no unique identifier is available in both data sets.

3. This definition implies that young individuals in the sample population had less time to accumulate pension entitlements than older persons, which is in line with the underlying idea of pay-as-you-go pension schemes.
4. In 2006, the SOEP group performed a pretest asking for the person's SSW. The question was not answered by more than 92 percent of the respondents. Further, the reliability of information collected from respondents is questionable as many provided information that was outside the expected range.
5. One short note on how the former GDR's pension scheme was incorporated into the system of old age provision of reunified Germany: Prior to reunification, East Germany's system had three pillars: one social insurance system that was far less generous than the West German scheme. In addition, the country had two special pension schemes (*Sonder- und Zusatzversorgungssysteme*) targeted at former GDR elites. With the German reunification, all entitlements accumulated in the former were fully integrated into the West German system, which involved a quite generous transfer of entitlements in order to assure an adequate standard of living of (future) retirees in East Germany. As a consequence, benefit payments for East German men are more or less comparable to levels in West Germany. East German women fare even better than West German women because of their more continuous fulltime labor force attachment.
6. Actively insured persons have at least one period of paid contributions (payment of compulsory or voluntary social insurance contributions, marginal employment) or creditable periods.
7. In occupational pension schemes, individuals can also accumulate SSW. These schemes typically are not compulsory and vary with respect to the replacement rate.
8. For 2010, the contribution level is 19.9 percent paid in equal parts by employee and employer.
9. The partner who earned higher pension rights transfers half of the difference in entitlements (deduction) to his or her former spouse (premium). In practice, women are the principal beneficiaries of pension splitting, because of their comparatively weaker labor market participation. For the majority of divorced couples, the splitting takes place right upon divorce; premiums and deductions remain unaffected by remarriage of either ex-partner.
10. The principle of equivalence, one of the guiding principles of the public pension system, implies that benefits are roughly equivalent to contributions paid into the system.
11. The replacement rate of civil servants who retire after forty years of full-time employment amounts to 72 percent of their last gross earnings. In contrast, the replacement level for the standard retiree (worked 45 years with average earnings) reaches approximately 48 percent of previous earnings.

12. A personal pension account is conditional on having at least one event over the life course that constitutes rights in the Statutory Pension Insurance.
13. SAPA data and Divorce Statistics provide the identifiers for record linkage.
14. For reasons of sample selectivity, SAPA is not the adequate recipient file. SAPA is selective for several reasons: First, certain groups are systematically excluded from having a pension account in the Statutory Pension Insurance. Second, account validation adds selectivity. The Statutory Pension Insurance asks every insured person to confirm the information stored in their account, but they are not obliged to do so. However, some people are more likely to validate than others. The authors restrict the analysis to validated pension accounts, which significantly reduces the sample size (336,069 instead of 568,586 observations). We accept the reduction in sample size, because validated accounts provide the most reliable information. For more information on account validation and selectivity, see Rasner et al. (2011).
15. Categorized continuous variables can also enter the imputation routine as a stratification variable. Any combination of stratification variables builds an imputation class or matching stratum. Both terms are used interchangeably. Cross-classification of a number of categorical variables can lead to many imputation classes, which possibly collides with an insufficient number of observations.
16. However, a further refinement might go in the direction of multiple imputations to better capture proper estimates of variance.
17. There are numerous names for this type of variables (also *cohort* or *stratification* variables). In the remainder of this article, the authors use the term *slice* variables. The groups are named matching strata or imputation classes.
18. In theory, one could increase the number of slice variables in the statistical matching. However, researchers face a trade-off: More imputation classes assure that matching partners are sufficiently similar in terms of slice variables (e.g., demographic or labor market attachment). However, more imputation classes might prevent observations from the recipient file to find the best matching partner in terms of the continuous matching variables in the donor data. This situation might occur if the best donor belongs to a different imputation class. In the literature, there is no evidence on how to balance the number of slice and matching variables. However, this question should be addressed formally in future research. In this particular application, we opted for six imputation classes in order to have a sufficient number of observations in each class to perform the benchmark tests.
19. Migrants are not divided into East and West Germany in order to assure a sufficiently high number of observations in the two migrant strata.
20. The Online Appendix (which can be found at http://smr.sagepub.com/supplemental/) provides summary statistics of slice and matching variables as well of the target variable.

21. This reverse completion of income information was necessary, because otherwise cases with missing values are excluded from the matching process. Furthermore, it improves the efficiency of the matching exercise assuming sufficient quality and representativeness of the imputed income data. However, it means that for some observations a significant portion of income information had to be imputed depending on when people entered the SOEP sample.
22. In the survey data at hand respondents report their monthly earnings, whereas in social security data earnings are cut at the maximum contribution ceiling, for example, the amount above which no additional social insurance contribution have to be paid and no additional entitlements are accrued. For 2007, the maximum contribution ceiling was fixed at €5,250 in monthly gross earnings for West Germany and €4,550 for East Germany (Deutsche Rentenversicherung 2010). For previous years, the income thresholds need to be adjusted accordingly with the respective year- and region-specific values.
23. Each credit is worth one earnings point, equivalent to the average earnings of all contributors in the respective year.
24. The authors are aware that the well-established hot deck imputation could be further refined. There are two reasons that justify the application of this simple hot deck variant: First, because the technique does not consider any of the available continuous matching variables it can provide valuable insights into the relevance of these variables to produce high-quality matches. The second reason for this simple hot deck approach is the limitation in the sample size. If we added another slice variable, such as grouped income, the size of the imputation slices would become too small for testing the performance of each technique.
25. The analysis does not apply record linkage in the traditional way using a unique identifier like the Social Security Number. However, with the combination of exact splitting amount, namely the splitting premium or deduction (measured in earning points with a precision of four decimal places), region (distinguishing 27 regional branches of the Statutory Pension Insurance), gender, and age, we generate a code that uniquely identifies individuals in the data and allows for a direct link of identical individuals in the divorce statistics and SAPA data.
26. Moreover, information from the *Divorce Statistics* would not contribute to an improvement of SOEP-SAPA matches. The divorce data do not contain any current information on the individual's marital status, even though this would certainly be an important slice or matching variable if it was included in SAPA data.
27. In the remainder of this article, the terms *observed* and *reported* benefits are used interchangeably. Both describe the public pension benefit information provided by SOEP respondents. As with all survey information, data are prone to response error.

28. We ran additional robustness tests to assess the stability of results by drawing five random samples with replacement and five disjoint random samples without replacement showing no notable variability. Results are available upon request.
29. In the Online Appendix (which can be found at http://smr.sagepub.com/supplemental/), Figure A1 provides Kernel density plots of the distribution of differences for each matching stratum. Results are satisfactory for larger slices, such as men and women in East and West Germany, whereas the two migrant strata with small numbers of observations fare poorly for all techniques. The Discussion section provides possible explanations for the bias in matches for male and female migrants.
30. Because of the small number of divorced migrants in our sample, those results are not further discussed.
31. Adding divorce as a slice variable is infeasible due to the small number of divorcees in the test population.
32. The shift is more significant for West than for East German divorcees, because pension splitting was only introduced in 1991 and confined to entitlements earned and marriages divorced thereafter.
33. Rässler and Kiesl suggest estimating the range of possible correlations of SSW and net worth within the Fréchet-Hoeffding bounds for the remaining observations for which the variables of interest are not jointly observed (Rässler and Kiesl 2006). This suggestion is worth testing; however, it goes beyond the scope of this article.
34. From this gross benefit, the Statutory Pension Insurance pays health and long-term care premiums and then transfers the net benefit to the retiree.
35. More than 50 percent of all new retirees face actuarial reductions for early retirement in 2010 (Deutsche Rentenversicherung 2010).
36. The robustness tests compared observed and matched pension benefits for individuals with different levels of labor market attachment. The results of these tests indicate that the matching quality is significantly better for individuals with a strong labor market attachment, defined as forty or more years of employment with income information throughout the observation period. In contrast, individuals with long periods of nonemployment and, consequently, zero income fare worse with respect to the matching quality. The results provide valuable insights for the explanations of differences in matching results across the matching strata.
37. SAPA data provide earnings information for the entire working life, in contrast to the SOEP, which started data collection in 1983 and 1991, respectively. For the matching, we only use earnings information for the years available in both data sets.
38. We also tested a matching algorithm exclusively restricted to income information. This variant rendered exceptionally good results for West German men,

underlining the predictive power of income for their final public pension benefit. Results are made available upon request.

39. Orlowski and Riphahn (2009) suggest that for many East German men job-specific human capital was outdated and did not match the requirements of the job market in unified Germany.
40. Given that the *production* of SAPA data is directly linked to administrative processes the available information is by nature more accurate, in particular when measuring short spells of unemployment. In the SOEP, respondents might not perfectly recall these shorter spells. Due to higher unemployment rates in East Germany following reunification, these differences in measurement might contribute to a greater difference between observed and matched pension benefit when compared to West Germany.
41. With a share of 92 percent, men were highly overrepresented in the special pension schemes and to a lesser extent so in the additional pension schemes with 54 percent (Seitz 2003).
42. The weak labor market attachment of West German women is reflected in the matching variables: For each year observed, more than half of this group has a pension-relevant income equal to zero.
43. Persons who worked and accrued pension rights in Germany and another country receive a so-called *Vertragsrente* (Himmelreicher 2005). Individuals qualify for the payment of such a pension if the two countries have a bilateral social security agreement (also *totalization agreement*).
44. In contrast to the SSW from the Statutory Pension Insurance, there is no comparable information such as the SAPA available for company pensions and entitlements for liberal professions. However, for the population of retirees, these pensions are directly surveyed in the SOEP. This procedure leads to an underestimation of SSW in the population of currently active members in the labour force.
45. So far, we only have the *gross* SSW for employees and civil servants. Their retirement income is subject to a differential tax treatment. The annuities of civil servants are already fully taxed. In contrast, life annuities, benefits from the public pension scheme, agricultural old age funds, or pension schemes organized by professional associations are taxed only to a certain degree (see §22 of the German Income Tax Act).
46. In alternative specifications, we vary this interest rate at 1 and 3 percent; the choice of the interest rate influences, by definition, the amount of the present value but changes little in the underlying relationships between SSW and occupational groups as described here (for more details, compare to Rasner et al. 2011). Entitlements from private pension schemes require no present value calculation, as this wealth component is already covered by the SOEP questionnaire.

47. The above calculations apply a discount rate of 2 percent. While this choice might appear normative, this value reflects the long-term real interest rate for federal bonds in Germany. Alternatively, an interest rate of 1 percent and 3 percent yields an aggregated net value of pension wealth of 6.5 and 4.9 trillion Euro, respectively. The corresponding mean values amount to about 91,000 and 68,000 Euro.
48. Other indicators such as the half-squared coefficient of variation (HSCV) or the P90 to P50 percentile ratio point in the same direction. For example, the results for HSCV are even more pronounced with 6.5 for net worth and 0.7 for SSW, mainly because of the top sensitivity of this indicator.
49. In the following section, a person's occupational status refers to the information provided in the SOEP individual questionnaire of 2007. It is however possible that a person has previously worked in another profession, which may affect the level of net worth and SSW.
50. Civil servants benefit to such a great extent from the inclusion of SSW because they typically enjoy a continuous employment career without any interruptions due to unemployment. Furthermore, the institutional design of the civil servants scheme accounts for their favorable position. In the final salary scheme, the last three years of earnings count, which are typically those years in which earnings peak. In contrast, the Statutory Pension Insurance takes the entire wage history into account.

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