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Map Intersection Based Merging Schemes for Administrative Data Sources and an Application to Germany

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Non–technical Summary

There are many situations in which the applied researcher wants to combine two different administrative data sources without knowing the exact link or merging rule. In particular, researchers often want to append data coded at different regional entities. One naive solution to this problem allocates a region coded at a particular regional classification to a region coded at another regional classification if these regions possess the largest intersecting area. However, such a naive merging rule based on simple visual inspection may be rather rough and could induce serious measurement errors.

This paper considers alternative merging rules based on intersecting maps of the corresponding regional classifications. The paper presents a number of alternative merging schemes based on the resulting intersection areas and some additional region-specific information (e.g. population density). However, typically, exact intersection areas are not available to the researcher, but need to be estimated from intersecting two digital maps. Depending on the properties of the underlying maps, i.e. the resolution and scale, such estimates may come with non-systematic measurement errors. This paper develops a theoretical framework for the estimation of map intersections and derives properties under which estimated intersection areas and weighting schemes that are based on these estimates are unbiased. A simulation study confirms our theoretical findings. Moreover, we identify conditions under which all merging schemes including the naive merging rule derive similar and reliable results. Under a high degree of local homogeneity in the region-specific information (e.g. population density) and under a high degree of similarity between the two regional classifications, all merging rules yield comparable results. A number of simulations demonstrates that with increasing local heterogeneity differences between merging schemes disappear.

As an empirical application, we use a map intersection of German counties and German labor office districts in order to investigate whether the theoretical results carry over to the empirical case. We estimate intersection areas using the software package ArcView. There is no systematic measurement error such that area estimates and merging schemes are unbiased. Still, estimation results may be sensitive to the choice of merging scheme. However, for an unemployment duration analysis based on the IAB employment sub-sample 1975-1997, we find that the effect of some merged regional characteristics are extremely robust with respect to the merging scheme applied. We conclude that in our particular case, a high degree of local homogeneity in the neighboring regions combined with a relatively high degree of similarity between both entities and a positive spatial autocorrelation of the regional characteristics even out any differences between the merging rules. The estimated weighting matrices for the merger of data from the federal Employment Office and the from federal Statistical Office is freely accessible to the research community and can be downloaded from $ftp://ftp.zew.de/pub/zew-docs/div/arntz-wilke-weights.xls$.

Map Intersection Based Merging Schemes for Administrative Data Sources and an Application to Germany*

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Abstract

In many situations the applied researcher wants to combine different data sources without knowing the exact link and merging rule. This paper introduces a theoretical framework how two different regional administrative data sources can be merged. It presents different merging schemes based on the area size of intersections between both regional entities. Estimates of intersection areas are derived from a digital map intersection. The theoretical framework derives conditions for the unbiasedness of estimated intersections and merging rules. The paper also presents conditions under which the choice of merging rule does not matter and illustrates the theoretical results with a simulation study. An application to German counties and federal employment office districts illustrates the applicability of the approach. It delivers merging schemes for regional data sources of the federal German statistical office and of the federal German employment office.

Keywords: map intersection, administrative data, merging schemes, estimation
JEL: C49, C89, R10

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1 Introduction

Applied research in economics often involves situations where we want to use region-specific variables coming from different data sources. Appending one variable to the other is non-trivial if the data sources are coded for different local entities for which no exact merging rule is available, i.e. it is not possible to simply aggregate regions of one classification to match the other classification. This is often the case if one wants to combine data coming from different administrative data sources. In this case, appropriate merging schemes need to be developed. Merging schemes require the availability of weighting matrices. These typically depend on the intersections of the local entities.

An easy solution applied by many researchers based on simple visual inspection are binary weights. This naive weighting scheme allocates a weight of one to a region's largest intersection area among all its intersection areas with the other regional classification and a weight of zero to all other intersection areas. However, this approach may be rather crude. As an alternative, this paper presents merging rules based on area size, population density and other criteria. Such merging rules can be easily calculated if the area size of all intersections between both regional classifications is known.

Typically, such intersection areas are not available from any administrative data source but need to be estimated from intersecting two digital maps. Thus, this approach requires maps of the corresponding regional classifications to be available. Depending on the properties of these maps, i.e. the resolution and scale, such estimates may come with non-systematic measurement errors. Since this paper is meant to be a guideline to researchers who need to tackle similar methodological issues, we develop a general framework for the estimation of map intersections that can be easily adapted to a multiplicity of contexts. We use this framework to derive at properties under which estimated intersection areas are unbiased.

We then propose several merging schemes based on these estimated intersection areas and derive how the measurement error of the underlying intersection areas affects estimated weighting schemes. We then discuss theoretical conditions under which estimated merging schemes yield reliable results even in the presence of estimation biases. These are the same conditions that ensure that even the naive merging rule derives at a reliable result. In fact, under a high degree of local homogeneity and/or similarity, a misspecification of the merging scheme is avoided and the choice of merging rule does not matter. Using a Monte Carlo simulation, we demonstrate the effect of local homogeneity on the proposed merging schemes.

In order to show that the theoretical results carry over to the empirical case, we conduct an application to German counties and labor office districts. The weighting matrices are determined based on estimates from a digital map intersection using the software package ArcView. In this application, the underlying map of labor office districts comes with a higher degree of generalization than the map of German communities. This introduces a measurement error, but does not systematically affect the estimated weighting schemes. A sensitivity analysis of the merging schemes shows that estimation results are not strongly affected by the choice of merging scheme. This may be attributed to some special conditions in the German context which tend to level out the differences.

The paper is structured as follows: section 2 presents the theoretical framework of the estimation of map intersections and it suggests merging rules with appropriate weights. Section 3 contains the application to German communities and labor office districts. Section 4 summarizes the main findings.

2 Theory

2.1 Estimation of map intersections

This subsection introduces the theoretical framework for the estimation of map intersections. We have two maps R and D. Each map contains a different disjoint regional classification of the same country. Denote $\{D_j\}_{j=1,\ldots,n}$ and $\{R_j\}_{j=1,\ldots,m}$ as two sequences of disjoint regions.

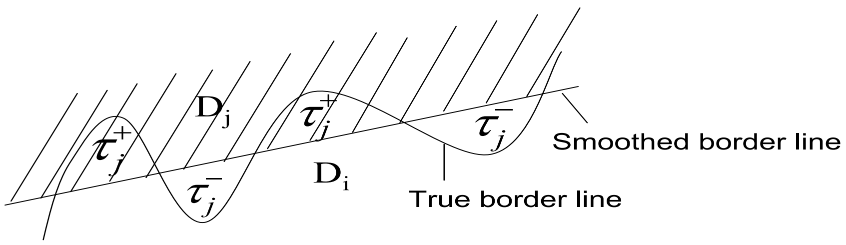
Let us denote μ as a measure of land area with the usual properties (Elstrodt, 1999, definition 4.1): $\mu(\varnothing) = 0$, $\mu(A) \leq \mu(B)$ for $A \subset B$ (monotonicity). For a sequence of subregions R_j (or D_j) we have

$$\mu(\bigcup_j R_j) \leq \sum_j \mu(R_j) \quad (\sigma\text{-additivity}).$$

The inequality holds with equality if R_j is a sequence of disjoint subregions. Then $\mu(R) = \mu(\bigcup_j R_j) = \mu(\bigcup_j D_j) = \mu(D)$. Our purpose is to determine $\mu_{ij} = \mu(D_i \cap R_j)$, the intersection size of regions D_i and R_j, for $i = 1, \ldots, n$ and $j = 1, \ldots, m$.

In our application we face the following difficulty: we don't know the true $\mu(R_j)$ and $\mu(D_j)$ and therefore we have to estimate them from map data using a GIS software package. The estimated areas may be affected by the properties of the underlying maps. In particular, maps usually come with a certain degree of generalization. The corresponding smoothing of the border lines generates a non-systematic error component whenever a part of region i is allocated to region j on the map. Moreover, maps may come with different degrees of generalization depending on the scale of the map. For the exposition of the theoretical framework, we assume the border lines of map R to be exact whereas the border lines of map D generate a non-systematic random error by smoothing the true border[1]. For this reason some part of D_j is allocated to D_i $(i \neq j)$ and vice versa. Figure 1 shows the areas that are falsely allocated to the neighboring region due to the smoothing of the border line.

Figure 1: Map generalization and the random measurement error



We assume that in expectation over two randomly chosen regions these errors balance out. Let us denote ϵ_j as the error set associated with region j, i.e. some subset of D_j that is misleadingly allocated to D_i, $i \neq j$, on the map. The error area $\mu(\epsilon_j)$ is therefore a stochastic measurement error. Also, note that $\mu(D_j \cap \epsilon_j) = 0$ since by definition D_j and ϵ_j are disjoint subsets. Moreover, ϵ_j is not necessarily a subset of D since at the outer border of the map ϵ_j may lie outside the territory of map D. Denote D^C as the complementary set of D, i.e. the area surrounding D, and let us denote $\tau_j^- = D_j \cap (\bigcup_i \epsilon_i \cup \epsilon^{D^C})$ and $\tau_j^+ = (D \cup D^C) \cap \epsilon_j$. The intersections with D^C and ϵ^{D^C} are relevant at the outer border of D only. We make three assumptions about the outer border line and the aggregated error area:

Assumption 1 *The measurement error does not systematically in- or decrease the area of any region, i.e.* $E\mu(\tau_j^+) = E\mu(\tau_j^-) \geq 0$.

Assumption 2 $\mu(D^C \cap \bigcup_j \epsilon_j) = \mu(D \cap \epsilon^{D^C})$, *i.e. the error area at the outer border of D balances out.*

In this paper, expectations are always taken over the regions and over the nonsystematic smoothing error of the border lines.

Let us denote $\hat{\mu}(A)$ as an estimate of $\mu(A)$.

Theorem 1 *Suppose assumptions 1-2 hold, then* $\hat{\mu}(R_j)$ *equals to* $\mu(R_j)$ *and* $\hat{\mu}(D_j)$ *is an unbiased estimator for* $\mu(D_j)$.

[1]The theoretical framework carries over to the more complex case with both maps introducing a random error due to the map generalization.

The first result is stable with respect to all unions of R_j and therefore also applies to $\bigcup_j R_j$. The second result is due to the observation $\hat{\mu}(D_j) = \mu(D_j) - \mu(\tau_j^-) + \mu(\tau_j^+)$ and assumption 1. We need an additional lemma before we come to $\hat{\mu}(D)$.

Lemma 1 *The error areas between the regions (ϵ_j) perfectly balance out, i.e.* $\sum_j \mu(\tau_j^-) = \sum_j \mu(\tau_j^+)$*).*

Proof.

$$
\begin{aligned}
\sum_j \mu(\tau_j^-) &= \sum_j \mu(D_j \cap \bigcup_i \epsilon_i) + \sum_j \mu(D_j \cap \epsilon^{D^C}) \\
&= \mu(D \cap \bigcup_i \epsilon_i) + \mu(D \cap \epsilon^{D^C}) \\
&= \mu(D \cap \bigcup_j \epsilon_j) + \mu(D^C \cap \bigcup_j \epsilon_j) \\
&= \mu(D \cup D^C \cap \bigcup_j \epsilon_j) \\
&= \sum_j \mu(D \cup D^C \cap \epsilon_j) \\
&= \sum_j \mu(\tau_j^+)
\end{aligned}
$$

where we use the properties of μ and assumption 2. ■

Theorem 2 *Suppose assumption 2 holds, then* $\hat{\mu}(D)$ *equals to* $\mu(D)$*.*

Proof.

$$
\begin{aligned}
\hat{\mu}(D) &= \hat{\mu}(\bigcup_j D_j) \\
&= \sum_j \mu(D_j) - \sum_j \mu(\tau_j^-) + \sum_j (\tau_j^+) \\
&= \mu(D),
\end{aligned}
$$

where lemma 1 immediately applies. ■

An interesting quantity is the relative bias of the size of D_j. Rewrite the previous equation for one particular area D_j as a fraction of its true area size $\mu(D_j)$:

$$
\frac{\hat{\mu}(D_j)}{\mu(D_j)} = 1 + \frac{\mu(\tau_j^+) - \mu(\tau_j^-)}{\mu(D_j)}.
$$

In expectation, the last term equals zero due to assumption 1. However in an application the distribution of this error may depend on the perimeter-size ratio of D_j.

A similar line of argument applies to the area size of the intersection of regions D_i and R_j if we make an additional assumption that slightly extends assumption 1.

Assumption 3 *The measurement error does not systematically in- or decrease the area of any intersection between R_j and D_i, i.e. $E\mu(\tau_i^- \cap R_j) = E\mu(\tau_i^+ \cap R_j) \geq 0$ for all i, j.*

This is a non crucial assumption if one considers that the partitioning of the regions into sub-regions as a result of the intersection between D_i's and R_j's not to systematically depend on the topology of the border lines. In the real world this is because administrative considerations typically form the basis of establishing border lines between sub-regions.

Theorem 3 *Suppose assumptions 2-3 hold, then $\hat{\mu}(D \cap R)$ equals to $\mu(D \cap R)$ and $\hat{\mu}(D_i \cap R_j)$ is an unbiased estimator for $\mu(D_i \cap R_j)$.*

Proof. The first part is shown by

$$\begin{aligned}
\hat{\mu}(D \cap R) &= \sum_{i,j} \hat{\mu}(D_i \cap R_j) \\
&= \sum_{i,j} \mu(D_i \cap R_j) - \sum_{i,j} \mu(\tau_i^- \cap R_j) + \sum_{i,j} \mu(\tau_i^+ \cap R_j) \\
&= \sum_{i,j} \mu(D_i \cap R_j) - \sum_{i} \mu(\tau_i^- \cap \bigcup_j R_j) + \sum_{i} \mu(\tau_i^+ \cap \bigcup_j R_j) \\
&= \sum_{i,j} \mu(D_i \cap R_j) - \sum_{i} \mu(\tau_i^-) + \sum_{i} \mu(\tau_i^+) \\
&= \mu(D \cap R),
\end{aligned}$$

where lemma 1 immediately applies. The second part follows from an application of the expectation operator to the second equality above together with assumption 3. ■

Again, rewrite the previous equation for one particular intersection area $\hat{\mu}(D_i \cap R_j)$ as a fraction of its true area size $\mu(D_i \cap R_j)$:

$$\frac{\hat{\mu}(D_i \cap R_j)}{\mu(D_i \cap R_j)} = 1 - \frac{\mu(\tau_i^- \cap R_j)}{\mu(D_i \cap R_j)} + \frac{\mu(\tau_i^+ \cap R_j)}{\mu(D_i \cap R_j)}$$

where the last two terms balance out in expectations due to assumption 3. As argued above, these two terms may affect the estimated intersection area in an application and higher moments of the error distribution may depend on the perimeter-area ratio of any D_j.

2.2 Weighting schemes for data merger

The purpose of this subsection is to present different merging schemes that merge information coded at D_j to information coded at the regions R_i[2] and to show how the required weighting matrices may be constructed. Available estimates of area sizes of $\hat{\mu}(D_j)$, $\hat{\mu}(R_i)$ and $\hat{\mu}(R_i \cap D_j)$ may be used to construct such weights. Information about the population density may also be incorporated. This section discusses how the estimation error of the map intersection affects such weighting matrices. We also consider a possible misspecification of the weighting schemes themselves, i.e. of the construction of weights, and derive at conditions under which such a misspecification does not affect the results.

Before discussing several possible merging schemes, note that there are two different kinds of information which have to be treated differently, i.e. which need to use different weighting matrices: frequencies (F) such as the number of job vacancies, participants in certain employment policies etc. and proportions (P) such as an unemployment rate.

Merging Schemes Without loss of generality, we focus on the case where we convert information from regions D_j to regions R_i. Let us denote $f_{i,j}$ and $p_{i,j}$ as weights with the usual properties: $f_{i,j}$ and $p_{i,j} \geq 0$, $\sum_i f_{i,j} = 1$ and $\sum_j p_{i,j} = 1$ for all i, j. The general rule for the merger of information for this case is

$$F_{R_i} = \sum_j F_{D_j} f_{i,j} \quad \text{for } i = 1, \ldots, n$$

where $f_{i,j}$ is an appropriate weight for frequency F_{D_j}, $j = 1, \ldots, m$ and

$$P_{R_i} = \sum_j P_{D_j} p_{i,j} \quad \text{for } i = 1, \ldots, n$$

where $p_{i,j}$ is an appropriate weight for proportion P_{D_j}, $j = 1, \ldots, m$. These merging schemes contain the special case of uniform weights $f_{i,j} = f_i$ or $p_{i,j} = p_i$ for all i. Uniform weights imply that F_{R_i} and P_{R_i} are simple averages over the F_{D_j} and P_{D_j}.

Construction of weights In an application there are several ways how the weights $f_{i,j}$ and $p_{i,j}$ can be constructed. We focus here on two approaches: naive binary weights and continuous weights that use the intersection size of regions R_i and D_j and an additional region-specific variable such as the population density.

[2] The vice versa case is not considered but our framework directly carries over.

First, consider naive binary weights. Region D_j is allocated to region R_i if they posses the largest intersection. In other words, we allocate a weight of one to the region D_j that shares the largest common area with R_i among all other intersecting regions. Obviously, $w_{i,j} = f_{i,j} = p_{i,j}$, where

$$w_{i,j} = \begin{cases} 1/\sharp_{i,j}\left(\mu(R_i \cap D_j) = \mu(R_i \cap D_l)\right) & \text{if } \mu(R_i \cap D_j) = \sup_{D_l} \mu(R_i \cap D_l) \\ 0 \quad \text{otherwise} \end{cases}$$

for all i, j, where $\sharp_{i,j}\left(\mu(R_i \cap D_j) = \mu(R_i \cap D_l)\right)$ is the number of sets D_l for which the equality holds. In an application we have typically $\sharp_{i,j} = 1$ for all i, j and therefore we refer to these weights as binary weights. They may be considered a rule of thumb and can be obtained by simple visual inspection.

Secondly, we suggest continuous weights that use information about the area size and intersection size of region R_i and D_j and another region-specific information, which is denoted as S_{R_i} and S_{D_j} in what follows[3]. For the merger of frequencies we suggest

$$f_{i,j} = \frac{\mu(R_i \cap D_j) S_{R_i}}{\sum_i \mu(R_i \cap D_j) S_{R_i}} \quad \text{for all } i, j$$

with an appropriately defined S_{R_i}. For the merger of proportions we suggest

$$p_{i,j} = \frac{\mu(R_i \cap D_j) S_{D_j}}{\sum_j \mu(R_i \cap D_j) S_{D_j}} \quad \text{for all } i, j$$

with an appropriately defined S_{D_j}. These weights include the special case in which the region-specific variable does not contain any information, i.e. $S_{R_i} = S_R$ or $S_{D_j} = S_D$ for all i, j. In this case the information is uniformly distributed across area space[4] and the weights simplify to

$$f_{i,j} = \frac{\mu(R_i \cap D_j)}{\mu(D_j)} \quad \text{for all } i, j$$

in the case of frequencies and to

$$p_{i,j} = \frac{\mu(R_i \cap D_j)}{\mu(R_i)} \quad \text{for all } i, j$$

in the case of proportions. These weights use information on the intersection and area size of R_i and D_j only.

[3]In an application one may use, for example, population densities, workplace densities or labor force densities as the region-specific information. The choice of information depends on the research question at hand. In the case of population densities, one may use $S_{R_i} = pop(R_i)/\mu(R_i)$, where $pop(R_i)$ is the number of individuals in R_i.

[4]For a given region i this requirement could be relaxed since it is only necessary that S_{R_i} does not vary in the neighborhood of i.

Estimation of weights The above weights can be estimated by replacing the true area sizes μ with their empirical counterparts $\hat{\mu}$. Naive weights can be estimated by

$$w_{i,j} = \begin{cases} 1/\sharp_{i,j}\,(\hat{\mu}(R_i \cap D_j) = \hat{\mu}(R_i \cap D_l)) & \text{if } \hat{\mu}(R_i \cap D_j) = \sup_{D_l} \hat{\mu}(R_i \cap D_l) \\ 0 \quad \text{otherwise.} \end{cases} \tag{1}$$

for all i, j.

Theorem 4 *Suppose assumptions 1-3 hold, then estimator (1) is unbiased, i.e.* $E\hat{w}_{i,j} = w_{i,j}$.

The proof is straightforward by taking expectations over $\hat{\mu}(R_i \cap D_j)$.
The estimator for the second continuous weight is given by

$$\hat{f}_{i,j} = \frac{\hat{\mu}(R_i \cap D_j) S_{R_i}}{\sum_i \hat{\mu}(R_i \cap D_j) S_{R_i}}, \tag{2}$$

for all i, j and for $\hat{p}_{i,j}$ analogously. Note that for simplicity we assume here that S_{R_i} and S_{D_j} are known numbers. Furthermore we require:

Assumption 4 *Assume that the measurement error of D_j intersected with any R_i is independent of the total measurement error of D_j for all i, j.*

From assumption 4 follows

$$E\left[\frac{\mu(\tau_j^+ \cap R_i) - \mu(\tau_j^- \cap R_i)}{\mu(\tau_j^+) - \mu(\tau_j^-)}\right] = 0$$

for all i, j.

Theorem 5 *Suppose assumptions 1-4 hold, then estimator (2) is unbiased, i.e.* $E\hat{f}_{i,j} = f_{i,j}$.

The proof uses the results of the previous subsection and assumption 4. Note that S_{R_i} and S_{D_j} are constants. In an application, however, $\hat{f}_{i,j}$ may be affected by the random measurement error of the map intersection.
We conclude that our proposed estimators have nice theoretical properties, i.e. they are unbiased. The estimates in an application are more precise if the underlying maps are exact. Note that the theorems directly carry over to the case of $\hat{p}_{i,j}$.

Misspecification of merging schemes Weights and thus merging schemes may not only be affected by the random measurement error of the underlying map intersection. The construction of weights, i.e. the merging schemes themselves, may be misspecified. Therefore, the question arises under which conditions such misspecifications result in large differences between the estimated frequencies F_{R_i} and proportions P_{R_i} across merging schemes and under which conditions the two merging schemes yield the same or very similar results. For this purpose we introduce the concept of local homogeneity and global heterogeneity with respect to information S.

Definition 1 *Local homogeneity with respect to information contained in S_i induces that $S_i \approx S_j$ for all i and all j in the direct neighborhood of i.*

Definition 2 *Global $c-$heterogeneity corresponds to*

$$sup_i \; inf_j \; |S_i - S_j| \leq c$$

for all regions i and all regions j in the direct neighborhood of i and any $c \geq 0$.

It is then evident that a small c implies local homogeneity for all regions i. Having this in mind it is easy to show that local homogeneity implies that the continuous merging scheme using the region-specific information S and the continuous merging scheme with a uniform distribution of S yield very similar results.

Definition 3 *Similarity of the regional entities R_i and D_j is defined by*

$$sup_{R_i}|\mu(R_i) - sup_{D_j}\mu(R_i \cap D_j)| < \epsilon$$

for all i, j and any $\epsilon > 0$.

Similarity of the regional entities suggests that weights are similar across all merging schemes. Clearly, if for all intersections i, j there is one large intersection that almost completely covers the reference region, differences between the two continuous and the naive weights tend to be small.

In practice, a combination of local homogeneity and similarity of the two regional entities may yield very similar weights for all merging schemes. On the other hand, it is clear that the naive weights are not reliable estimates in case of non-similarity of the regional entities. Moreover, all proposed merging schemes may be inappropriate if there is local heterogeneity within the regions. This, however, is not modelled here and with increasing similarity of the regional entities it becomes less relevant.

Monte Carlo Evidence It is interesting to investigate how the proposed weighting schemes affect the results when the true value is known. For this reason we perform a series of simulations for the prediction of frequency F_R. In order to make the simulation results comparable to our application in the following section we use here the same regional classification for R and D. The number of sets R_i and D_j and the set of intersections is therefore identical to the empirical framework. The remaining simulation framework is chosen as follows:

- maximum dissimilarity of regional entities conditional on the set of intersections. This implies equal intersection areas for a given R_i, i.e. $\mu(R_i \cap D_j) = \mu(R_i \cap D_l)$ for all l s.t. $\mu(R_i \cap D_l) > 0$.
- $F_D \sim U(900, 1100)$ is discrete random variable, i.e. no autocorrelation in F_{D_j}.
- the error of the estimated intersection sizes follows a normal distribution: $\hat{\mu}(R_i \cap D_j) - \mu(R_i \cap D_j) = \epsilon_{i,j}$, where $\epsilon_{i,j} \sim N(0, \mu(R_i \cap D_j))$. This error is resampled in each repetition of the 500 simulations.
- S_R is drawn according to three different designs of spatial autocorrelation:
  - *i)* $S_R = 1$, no variation in the region-specific information.
  - *ii)* S_R is drawn element by element from $N(5, 0.5)$. If there is already a S_R assigned to the direct neighborhood of S_{R_i} we compute $S_{R_i} = 0.2\epsilon_{R_i} + \bar{S}_{R_i}$, where $\epsilon_R \sim N(0, 0.5)$ and $\bar{S}_{R_i}$ is the average over all neighboring and already assigned S_{R_i}. This simulation design induces a weak spatial autocorrelation which is confirmed by a Moran's I statistic. Accordingly, there is significant clustering of similar values of the region-specific information S_{R_i}[5].
  - *iii)* $S_R \sim N(5, 0.5)$, random variation in the region-specific information,

Simulation designs *i*-*iii* allow us to evaluate the relevance of the information S_R in an application. Simulation results are presented in table 1, where we relate the resulting $\hat{F}_R$ to their values. The true values are computed with the exact $\mu(R_i \cap D_j)$ and the correct merging scheme, which is always the continuous weighting scheme that uses the region-specific information. The bias and higher moments of the distribution are therefore due to the errors in

[5] We calculate Moran's I using different weights for the spatially lagged vector. Using a weight of one for regions within a 0.5 degree radius of the grid location of the county, we get a test statistic of 0.23 ($z = 7.0$). Using a 1 degree radius the test statistic falls to 0.15 ($z = 9.6$) but again is highly significant. 0.1 degree correspond to 11.1 km along the longitude and between 6.5 to 7.5 km along the latitude. Clearly, using the grid position for the weighting scheme is a somewhat crude but justifiable approach.

the map or due to the misspecification of the weighting scheme. In particular, the continuous weights that use the region-specific information deviate from the true weights only due to the measurement error in the map, while the other weighting schemes may be affected by a combination of measurement errors and misspecification. Table 1 clearly supports our theoretical framework that the measurement error in the maps does not bias estimation results if the weighting scheme is correctly specified. As expected for our simulation design, the naive estimator performs poorly in our simulation framework. We also observe that the continuous weighting scheme always behaves better. However, ignoring region-specific information biases results and the variance increases slightly. Only the third weighting scheme behaves properly in all designs. However, in case of spatial autocorrelation in F_D and similarity of the regional entities, both continuous schemes as well as the naive estimator produce similar results[6].

Table 1: Monte Carlo Evidence for the distribution of $(\hat{F}_R - F_R)/F_R$

	Mean	Sd	MSE‡	MSE‡in % of *i*
Simulation i				
Naive weights	−0.2417	1.5350	2.4146	100%
Cont. weights, $S_{R_i} = 1$	−0.0001	0.0436	0.0019	100%
Cont. weights	−0.0001	0.0436	0.0019	100%
Simulation ii				
Naive weights	−0.2369	1.5166	2.3562	97.6%
Cont. weights, $S_{R_i} = 1$	0.0035	0.0682	0.0047	247.4%
Cont. weights	−0.0000	0.0436	0.0019	100%
Simulation iii				
Naive weights	−0.2331	1.5337	2.4066	99.7%
Cont. weights, $S_{R_i} = 1$	0.0085	0.0965	0.0094	494.7%
Cont. weights	−0.0000	0.0436	0.0019	100%

‡ Mean squared error

We conclude that without any precise information on the spatial distribution of the data and the degree of similarity of the regional entities, there is no way to tell how strongly research results are affected by the choice of merging scheme. In empirical applications, a

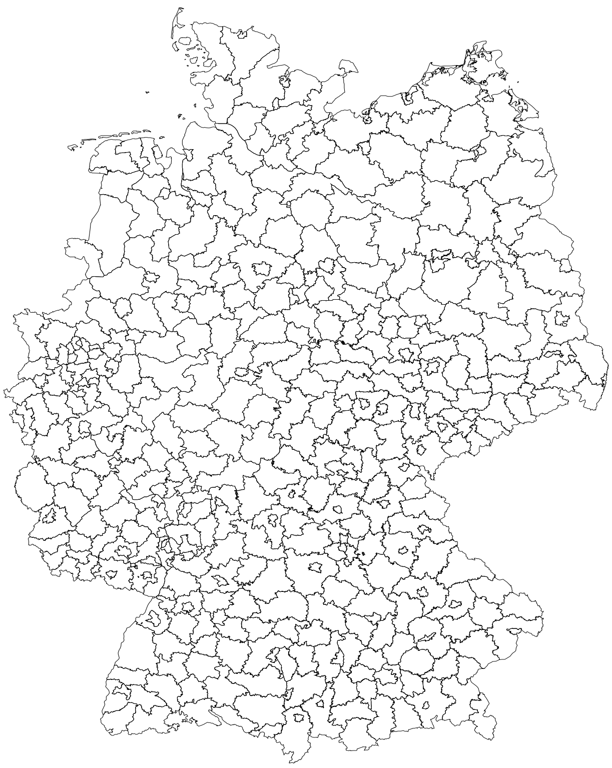
[6]These cases are not presented but results are available on request.

sensitivity analysis may be useful to investigate the robustness of research results based on the chosen merging scheme. Our simulation results suggest that higher moments of the error distribution are also affected by the choice of the weighting scheme.

3 Empirical application

The purpose of the empirical application is twofold. First of all, we want to show how the above framework may be easily applied to any particular case. Secondly, we want to perform a sensitivity analysis in order to test the robustness of estimation results with regard to the choice of merging scheme and discuss the results in light of the above theoretical considerations.

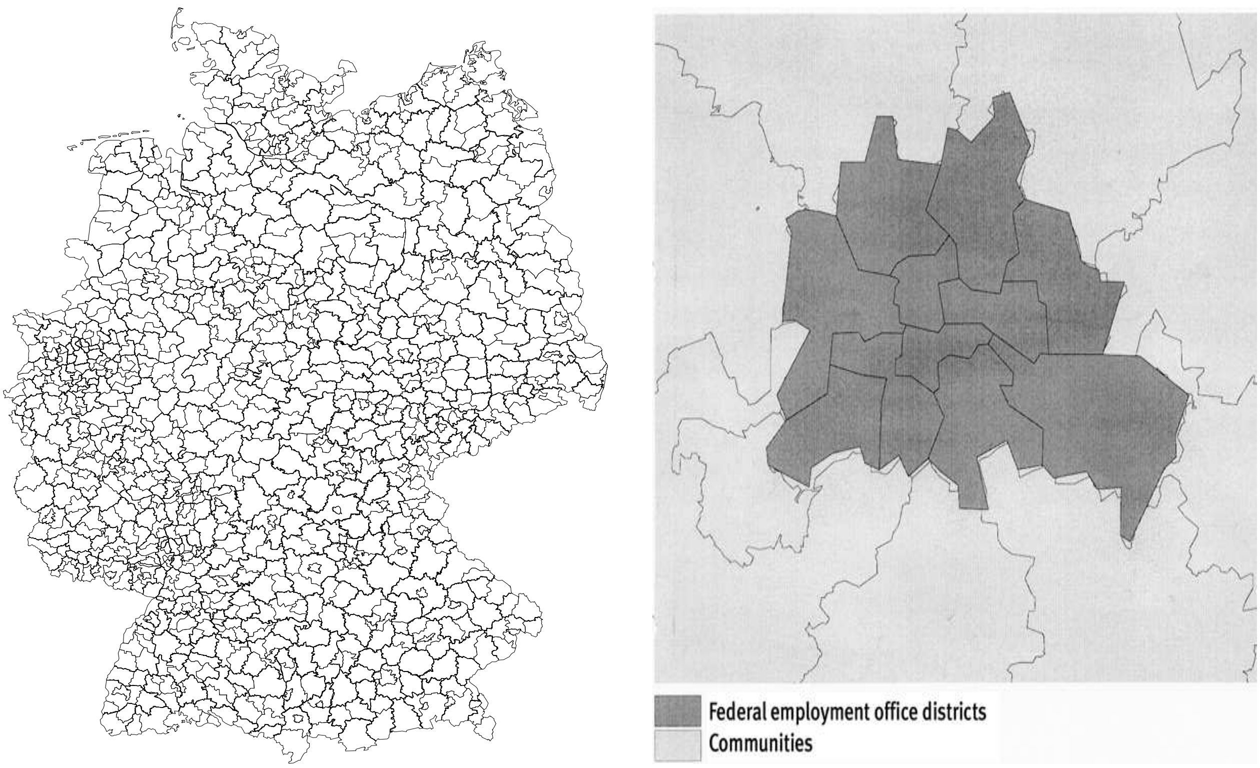
Figure 2: The German Communities (left) and the German federal employment office districts (right)



As an empirical application we use two maps of distinct regional entities in Germany (see figure 2), a map of German counties (Kreise) and a map of federal employment office districts (Arbeitsamtsdienststellen). Both of these regional entities are important data sources for researchers in labor economics, other fields of economics and social sciences alike. Typically, microdata are coded at the level of the German counties while important labor market characteristics are coded at the level of the federal employment office districts. Unfortunately, counties and labor office districts intersect each other and there is no exact merging rule available. Thus, we have a prime field of application for deriving a merging rule based on intersecting two digital maps.

The theoretical framework that has been developed in the previous section can easily be applied to the intersection of these two maps. Think of the German counties as the R_i regions with $i = 1, \ldots, 440$ disjoint entities. The federal employment office districts correspond to the D_j regions with $j = 1, \ldots, 840$. In order to develop merging rules based on this intersection, we estimate the area size of the counties R_i, the districts D_j and their intersections $\hat{\mu}(R_i \cap D_j)$ using the software package ArcView. Figure 3 to the right shows the resulting map from intersecting counties and districts. This intersection results in more than $3,600$ subregions.

Figure 3: The intersection of German Communities and German federal employment office districts (left) and stochastic measurement error at the Berlin border lines (right)



In line with the theoretical framework, the district map D comes with a larger scale than the county map R[7]. However, both maps come with a scale that involves some smoothing

[7]In our particular case, map D was not available electronically such that we scanned the map in a raster

of the border lines. This slightly extends the theoretical framework with two instead of one source of random noise, the border lines of D_j as well as the border lines of R_i. This measurement error can be seen at the border line of the Berlin area (see figure 3 to the right). Moreover, the stochastic measurement error now is also relevant at the outer border of Germany. Still, the spirit of our theoretical framework directly carries over to this application.

In particular, we expect area estimates not to show any systematic biases, but to be very close to the true area sizes on average. Thus, as a first step, we compare the total estimated area of both maps R and D, i.e. $\hat{\mu}(R)$ and map D $\hat{\mu}(D)$, to the known exact area size of Germany. On this aggregate level, estimates may deviate from the true area size due to the stochastic measurement error at the outer border line of Germany. The following table shows the exact area size of Germany, the area estimates and the corresponding percentage deviations.

Table 2: True and estimated area size of Germany (in km^2).

	$\mu(G)$	$\hat{\mu}(R)$	$\hat{\mu}(D)$
Area size in km^2	$357,020.8$	$357,382.0$	$357,305.5$
Percentage deviation		$+0.1$	$+0.1$

Table 2 shows that estimates $\hat{\mu}(R)$ and $\hat{\mu}(D)$ overestimate the German area size. Apparently, in our case, the error areas at the outer border of D and R do not balance out, but slightly increase the estimated area size. However, at least on this aggregate level, the estimated area is very close to the true area size of Germany. Estimates deviate by 0.1% from this benchmark only. Yet, for any particular sub-region, this stochastic measurement error need not be negligible. However, there should be no systematic measurement error involved.

Thus, as a next step, we examine the measurement error involved in estimating regional area sizes by comparing $\hat{\mu}(R_i)$ to its exact area size $\mu(R_i)$. We use area sizes that are officially released as the county areas by the federal German statistical office (Statistik Regional,

data format. Afterwards we the raster data have been converted to vector data. This conversion does not produce any systematic errors so that consistent with the theoretical framework, the measurement error along the border lines may be considered random.

1999) as a measure of $\mu(R_i)$. Table 3 shows the summary statistics of $\hat{\mu}(R_i)$, $\mu(R_i)$ and their percentage deviation.

Table 3: Comparing the estimated to the true area size of 440 German counties.

	Mean	Std. dev.	25th pct.	50th pct.	75th pct.	Min	Max
$\hat{\mu}(R_i)$	812.23	599.28	264.1	760.5	1186.5	35.7	3073.6
$\mu(R_i)$	811.15	596.97	262.1	759.5	1188.7	35.6	3058.2
$\frac{\hat{\mu}(R_i)-\mu(R_i)}{\mu(R_i)} * 100$	-0.075	2.180	-0.214	0.048	0.313	-19.764	10.275

Comparing the summary statistics for $\hat{\mu}(R_i)$ and $\mu(R_i)$, suggests that, on average, the estimated and true areas are remarkably similar again with a percentage deviation of less than 0.1%. However, note that there are some rather extreme outliers in both directions. In particular, we find that some Eastern urban areas such as Chemnitz, Zwickau, Görlitz, Stollberg, Wartburgkreis and Leipzig are among these outliers. Apparently, there is a problem with some Eastern areas stemming from the fact that there have been various reforms during the last decade to spatially restructure the county. What we considered the exact area sizes $\mu(R_i)$, may therefore not reflect the true area size for some Eastern regions since the data source for the exact measure $\mu(R_i)$ (Statistik regional, 1999) does not correspond to the same point in time as the map used for the map intersection which corresponds to 1996. Thus, excluding the Eastern areas should eliminate some of the major outliers. This is indeed the case. The remaining outliers unsurprisingly tend to be coastal areas such as Lübeck and Bremerhaven. For coastal areas which typically possess a natural border line, the smoothing of the border lines may be expected to result in larger error components than for other regions. Apart from this aspect, no systematic relationship between the measurement error and any regional characteristic (e.g. perimeter-area ratio) can be found. Thus, as predicted by the theoretical framework, area estimates seem to be unbiased.

We conclude that for some (coastal) sub-regions the smoothing of the border lines results in pronounced under- or overestimation of the true area size due to the stochastic measurement error involved. However, on average, this stochastic component is very small. Moreover, no systematic influences could be detected. This suggests that, in line with the theoretical predictions, area estimates and the corresponding weighting schemes are unbiased.

Sensitivity Analysis Due to the possibility of misspecifying merging schemes, even unbiased weights may produce false results. Put differently, unbiasedness does not tell us anything about the best choice among the various merging schemes. Ultimately, whether a particular merging schemes is preferable compared to an alternative scheme depends on the degree of similarity and local homogeneity in the underlying spatial context. As presented in section 2.2, a high degree of similarity between two types of regions as well as a high degree of local homogeneity render differences between merging schemes negligible. Under such conditions, even a naive merging scheme may be an appropriate choice. Otherwise, only a sensitivity analysis reveals whether estimation results are robust with respect to the merging scheme used.

Therefore, this section conducts a sensitivity analysis of the effect of certain regional labor market characteristics on the job-finding hazard of unemployed individuals in West Germany (excluding the Berlin area) between 1981 and 1997. The micro data set used for the analysis is the IAB Employment Subsample (IAB-Beschäftigtenstichprobe) 1975 to 1997. See Bender et al. (2000) for a detailed discussion of the data. The data set contains daily register data of about 500,000 individuals in West-Germany with information on their employment spells as well as on spells during which they received unemployment insurance. The data set is a representative sample of employment that is subject to social security taxation and excludes, for example, civil servants and self-employed individuals. All individual information is coded at the level of the so called micro-census regions. These regional sub-divisions lump together up to four communities. There are 270 micro-census regions in West Germany. Regional labor market related variables, however, are coded at the level of labor office regions. These regions consist of labor office districts and typically lump together three to four labor office districts to one labor office region. In order to merge the micro data set coded at the level of the 270 microcensus regions with regional data coded at the level of the 141 labor office regions, we can use the map intersection of German labor office districts and counties. This is, we aggregate the estimated areas to the level of microcensus and labor office regions and use the corresponding intersection estimates as the basis for the merging rules proposed in section 2.2. Intersecting these two regional entities yields a total of 1.149 sub-regions.

There are two possible reasons why estimated weights might not differ substantially between alternative weighting schemes. First of all, there may be a high degree of local homogeneity in the region-specific information that is used for the continuous weighting scheme. Here, we use regional labor force densities as the region-specific information S. Indeed, labor force densities between counties, for example, do not tend to change abruptly. Using a Moran's I statistic[8], we find evidence in favor of a clustering of similar values, i.e. areas with

[8]See footnote on page 11 for details on the test statistic. Using a weight of one for regions within a 0.4

high (low) labor force densities tend to be close to other regions with high (low) densities. Apparently, there is a high degree of local homogeneity or a low level of c-heterogeneity in the underlying region-specific information S (see section 2.1). As a consequence, differences between weights that do or do not use this region-specific information should be rather small.

Secondly, we may also expect differences between the naive and the two continuous merging schemes to be rather small. This is because the intersected regional maps do show a high degree of similarity (see figure 2). In several cases, counties do not even intersect with a labor office region or only have small intersections with one additional labor office region. As a consequence, the naive merging scheme may be relatively close to the continuous weighting schemes.

Indeed, we find that the resulting weights on average do not differ substantially. In fact, weights based on the merging rule that uses region-specific information shows an extremely similar distribution to the weights assuming a uniform distribution of the region-specific information with an average value that differs only in the 10th decimal place. Standard deviations, percentiles as well as minima and maxima are also quite similar. However, while on average the merging rule does not appear to be very influential, weights differ substantially between merging rules for some sub-regions for which there is a low degree of local homogeneity within the neighboring area. Table 4 looks at an example to demonstrate this point.

Table 4: Weighting schemes $\hat{f}_{i,j}$ for the Bremen labor office region

Labor office region	Micro census region	$\hat{S}_{R_i} = 1$	$\hat{S}_{R_i} = \frac{lf(R_i)}{\hat{\mu}R_i}$	Naive
Bremen	Bremen	.31311	.83763	1
Bremen	Diepholz	.00189	.00039	0
Bremen	Wesermarsch	.01382	.00208	0
Bremen	Osterholz	.65232	.15748	1
Bremen	Rotenburg	.01576	.00169	0
Bremen	Verden	.00309	.00073	0

Bremen is a large city in the north of Germany with around 500,000 residents and a relatively high labor force density compared to the surrounding rural areas (Diepholz, We-

degree radius of the grid location of the county, we get a test statistic of 0.21 ($z = 5.3$). Using a 0.8 degree radius the test statistic falls to 0.16 ($z = 8.9$) but again is highly significant.

sermarsch, Osterholz, Rotenburg, Verden). Thus, while around 31 % of the area of the Bremen labor office region intersects with the micro-census region of the same name, taking account of the fact that most of the labor force of the labor office region works in this intersecting area results in a weight of almost 84 %.

We conclude at that point that, on average, the weighting factors do not differ substantially at all. Apparently, in most cases, labor force densities in neighboring and intersecting regions are relatively homogenous or the underlying regions are relatively similar so that all schemes result in very similar weighting matrices. However, for some selective regions with a high degree of heterogeneity in the region-specific information within the local neighborhood, the choice of merging rule may have an important influence. We therefore decide to look at two different samples for the sensitivity analysis, a full and a selective sample. The full sample includes all 255,100 unemployment spells [9] produced by 126,189 individuals and beginning between 1981 and 1997 in any West German micro-census region[10]. The selective sample includes only unemployment spells from those micro-census regions whose estimated weighting schemes differed substantially[11]. Given the above results, we expect the analysis based on the full sample to be more sensitive with respect to the weighting scheme than for the heterogeneous subsample. However, even for the selective sample, estimation results may be quite robust if the regional data to be converted, F_{D_j} and P_{D_J}, does not vary significantly between adjacent and nearby regions.

There are two regional labor market indicators that are coded at the labor office regions and which need to be converted to micro-census regions: the unemployment rate (P_{D_j}) and

[9]Periods of registered unemployment cannot be identified easily given the data structure of the IAB employment subsample. This is because we only observe periods of dependent employment and periods of transfer payments from the labor office, but do not observe any information on the labor force status of the individuals during these spells or during the gaps between spells. For a detailed discussion of these problems see Fitzenberger and Wilke (2004). For our purpose, we define an unemployment spell as all episodes after an employment spell during which an individual continuously receives transfer payments. There may be interruptions of these transfer payments of up to four weeks - in the case of cut-off times up to six weeks. Moreover, the gap between employment and the beginning of transfer payments may not exceed 10 weeks. The gap between the end of transfer payments and the beginning of employment may not exceed 12 weeks. Otherwise, the unemployment spell is treated as censored when transfer payments end. This is a reasonable restriction because longer gaps may mean that individuals temporarily or permanently left the labor force or that they became self-employed in which case we do not observe them any longer in our sample.

[10]The sample has been restricted to individuals aged 18-52 at the beginning of the unemployment spell.

[11]A micro-census region belongs to the selective sample if either the absolute deviation between $\hat{f}_{i,j}(S = const.)$ and $\hat{f}_{i,j}(S \neq const.)$ or the absolute deviation between $\hat{p}_{i,j}(S = const.)$ and $\hat{p}_{i,j}(S \neq const.)$ is above the 99th or below the 1st percentile.

the ratio of unemployed individuals to vacancies in the region (F_{D_j}). Both indicators are proxies for labor market tightness and may be expected to have a significant negative effect on the job-finding hazard of unemployed individuals in West Germany. As mentioned above, the degree of spatial correlation may have a strong effect on the robustness of estimation results with respect to the choice of merging scheme. For this reason, we look at a Moran's I statistic for both regional indicators and find significant spatial clustering of similar values[12]. As a consequence, even for a selective sample of regions for which weighting matrices differ significantly, the converted regional data F_{R_i} and P_{R_i} might be quite similar for different merging schemes.

Table 5: Summary statistics of unemployment rates for the full and the selective sample by merging scheme

Weights	$\hat{S}_{R_i}$	Obs.	Mean	Std. dev.	Min	Max
Full Sample						
$\hat{f}_{i,j}$	1	270	7.864	2.833	3.183	15.757
$\hat{f}_{i,j}$	$\frac{lf(R_i)}{\hat{\mu}R_i}$	270	7.890	2.848	3.172	15.760
Naive	-	270	7.873	2.864	3.167	15.767
Selective Sample						
$\hat{f}_{i,j}$	1	14	9.226	3.646	3.905	15.009
$\hat{f}_{i,j}$	$\frac{lf(R_i)}{\hat{\mu}R_i}$	14	9.245	3.679	3.917	14.769
Naive	-	14	9.227	3.809	3.933	14.333

Indeed, summary statistics of the converted unemployment rate P_{R_i} and the converted unemployment-vacancy ratio F_{R_i} at the level of micro-census regions (see table 5 and 6) suggest that differences between merging schemes are levelled out. Even for the selective sample of 14 micro-census regions for which the weights differed most, there is not much variation across the weighting schemes. There is some more variation in the selective sample for the unemployment-vacancy ratio than for the unemployment rate. Still, summary statistics are quite similar across merging schemes. This suggests that estimated effects of the

[12]Again (see footnote on page 11) we calculate Moran's I using different weights for the spatially lagged vector. Using a weight of one for regions within a 0.4 degree radius of the grid location of the county, we get a test statistic of 0.85 ($z = 16.3$). Using a 0.8 degree radius the test statistic is 0.72 ($z = 31.4$) which again is highly significant.

unemployment rate and the unemployment-vacancy ratio on the unemployment duration of West German job seekers should be very robust across merging scheme, even for the selective sample.

Table 6: Summary statistics of unemployment/vacancy ratio for the full and the selective sample by merging scheme

Weights	$\hat{S}_{D_i}$	Obs.	Mean	Std. dev.	Min	Max
Full Sample						
$\hat{p}_{i,j}$	1	270	8.371	5.121	1.723	30.803
$\hat{p}_{i,j}$	$\frac{lf(D_j)}{\hat{\mu}D_j}$	270	8.372	5.109	1.730	31.001
Naive	-	270	8.544	5.484	1.720	31.494
Selective Sample						
$\hat{p}_{i,j}$	1	14	9.833	6.788	1.727	25.023
$\hat{p}_{i,j}$	$\frac{lf(D_j)}{\hat{\mu}D_j}$	14	10.064	6.625	1.733	24.994
Naive	-	14	11.549	8.178	1.720	25.278

For the sensitivity analysis, we estimate a proportional hazard model where the baseline hazard includes a common fixed effects for individuals in the same labor market region[13]. This may be estimated using Cox's partial likelihood estimator (Cox, 1972). Including location-fixed effects in this estimator removes a potential bias of individual and labor market related variables that may result from omitting important regional labor market characteristics (Kalbfleisch and Prentice, 1980; Ridder and Tunali, 1999). In addition to the location-specific fixed effects we also take account of the fact that some individuals have repeated unemployment spells. Thus, we use the modified sandwich variance estimator to correct for dependence at the level of the individual (Lin and Wei, 1989).

Table 7 summarizes estimation results for the unemployment rate and the unemployment-vacancy ratio for the full sample and the three merging schemes. We control for education, sex, age, marital status, occupational status, economic sector, a set of year dummies as well as some indicators of prior employment history including total previous unemployment duration, tenure in the previous job and an indicator variable of whether there has ever been

[13]We use labor market regions instead of microcensus regions because labor market regions are likely to be the relevant regional context in which individuals mainly seek employment. There are a total of 180 West-German labor market regions.

a recall from the previous employer. Summary statistics and estimation results using the full and the selective sample can be found in the appendix[14].

Table 7: Cox PH model estimates for regional indicators by merging scheme and sample

	Full Sample		**Selective Sample**	
Merging Scheme	**Haz. Rat.**	**Std. Err.**	**Haz. Rat.**	**Std. Err.**
Unemployment-vacancy ratio				
$\hat{f}_{i,j}$ with $S_{R_i} = 1$	0.989^{**}	0.000	0.986^{**}	0.001
$\hat{f}_{i,j}$ with $S_{R_i} \neq 1$	0.989^{**}	0.000	0.985^{**}	0.001
Naive	0.989^{**}	0.000	0.987^{**}	0.001
Unemployment rate				
$\hat{f}_{i,j}$ with $S_{D_j} = 1$	0.967^{**}	0.001	0.971^{**}	0.005
$\hat{f}_{i,j}$ with $S_{D_j} \neq 1$	0.966^{**}	0.001	0.973^{**}	0.005
Naive	0.967^{**}	0.001	0.976^{**}	0.005

Significance levels : † : 10% $*$: 5% $**$: 1%

As expected from the above discussion, the effect of the unemployment rate and the unemployment-vacancy ratio on the job finding hazard is extremely robust across the different weighting schemes for the full and the selective sample. In our empirical application the merging scheme applied has no impact on the estimated hazard ratios up to the 4th decimal place for the full and up to the 3rd decimal place for the selective sample. This even holds for the naive merging scheme.

We conclude that, at least in the case of a merging rule between German districts and counties, the choice of merging rule does not substantially affect our estimation results. In our specific application it even seems safe to take the simplest approach available to the researcher: a merging rule based on simple binary weights. However, due to a high degree of local homogeneity in S, a high degree of similarity of the regional entities and a strong positive spatial autocorrelation of the data to be merged, this is likely to be a result that is unique to this particular application. Other countries, for example, may be much more heterogeneous across space with regard to labor-force densities. Also, other regional

[14]Since estimation results across the various specifications are very similar, the appendix only includes detailed results for the Cox model using the unemployment rate as the regional labor market variable in addition to the individual-specific characteristics. Moreover the estimation results only show the case of merging the unemployment rate based on a uniform distribution of the region-specific information.

entities may be less similar. Thus, researchers applying the above approach to a different set of regional entities should be aware that these factors have an important effect on the robustness of their results. Also, they should check the degree of spatial autocorrelation of the data that has to be merged. If there is spatial clustering of dissimilar values, estimation results are likely to be much more sensitive to the choice of merging rule than in our particular application. Therefore, researchers are advised to carefully apply the theoretical framework to their context and examine the conditions of local homogeneity, similarity of regional entities and positive or negative spatial autocorrelation in detail before choosing one of the above merging schemes. Moreover, a sensitivity analysis is always advisable.

4 Conclusion

This paper introduces a theoretical framework for merging different regional data sources for which no exact merging rule is available. It therefore tackles a substantial problem for empirical work in labor economics, other fields of economics and social sciences alike. The combination of data sources often allows the researcher to choose a broader econometric modelling approach such as allowing for region-specific effects.

We introduce alternative merging rules based on estimates of intersections between both regional classifications. Such estimates may be obtained from a digital map intersection. Depending on the properties of the underlying maps, i.e. the resolution and scale, we show that such estimates may come with non-systematic measurement errors. This paper develops a theoretical framework for the estimation of map intersections and derives properties under which estimated intersection areas and weighting schemes that are based on these estimates are unbiased. Moreover, we identify conditions under which all merging schemes including the naive merging rule derive comparable and reliable results. Under a high degree of local homogeneity in the region-specific information (e.g. population density) and under a high degree of similarity between the two regional classifications, differences between merging schemes are levelled out. A Monte Carlo simulation demonstrates our theoretical findings. Moreover it shows for different degrees of local homogeneity that estimation results can substantially differ depending on the chosen merging scheme.

We apply our theoretical framework to the maps of German counties and employment office districts and show that our theoretical results carry over to the empirical case. Performing an unemployment duration analysis using the IAB employment subsample merged with regional data from the federal statistical office shows that the chosen weighting scheme does not significantly affect the estimation results (on average and for a specific subsample). This result is well explained by our theoretical model.

The estimated weighting matrices for merging data from the federal Employment Office and the from federal Statistical Office is freely accessible to the research community and can be downloaded from $ftp://ftp.zew.de/pub/zew-docs/div/arntz-wilke-weights.xls$

5 Appendix

Table 8: Summary statistics for the full and the selective sample of unemployment spells, IAB employment subsample, 1981-1997

	Full Sample		**Selective Sample**	
	Mean	**Std. Err.**	**Mean**	**Std. Err.**
Unemployment duration (in days)	293.24	443.86	285.55	407.46
Female	0.41	0.49	0.44	0.50
Married	0.46	0.50	0.44	0.50
Married female	0.21	0.41	0.21	0.41
Age < 21	0.08	0.28	0.07	0.26
Age 21-25	0.23	0.42	0.21	0.41
Age 31-35	0.14	0.35	0.14	0.35
Age 36-40	0.11	0.31	0.13	0.32
Age 41-45	0.10	0.30	0.11	0.31
Age 46-49	0.07	0.26	0.08	0.27
Age 50-53	0.08	0.27	0.08	0.27
Low education	0.38	0.49	0.36	0.48
Higher education	0.04	0.20	0.05	0.23
Low educ. x Sex	0.16	0.37	0.17	0.37
High. educ. x Sex	0.02	0.13	0.02	0.15
Apprenticeship	0.07	0.25	0.06	0.25
Low skilled worker	0.34	0.48	0.32	0.47
White collar worker	0.25	0.43	0.30	0.46
Parttime work	0.08	0.27	0.09	0.28
Agriculture	0.03	0.17	0.02	0.13
Inv. goods industry	0.20	0.40	0.17	0.38
Cons. goods industry	0.12	0.32	0.08	0.28
Construction	0.15	0.36	0.12	0.33
Services	0.31	0.46	0.38	0.49
Tenure in previous job (in months)	27.20	38.09	26.88	38.64
Previous recall	0.06	0.23	0.05	0.22
Total unemp. duration (in months)	8.43	15.03	8.29	14.70
1983-1987	0.32	0.47	0.32	0.47
1988-1991	0.19	0.39	0.19	0.39
1992-1997	0.34	0.47	0.34	0.47
Unemployment rate[a]	9.70	3.38	9.34	3.56
Number of spells	255,100		83,104	
Number of individuals	126,189		24,674	
Percentage right-censored	28.4		29.7	

[a] Regional information has been merged using the uniform distribution of the region-specific information $S_{D_j} = 1$.

Table 9: Cox PH model estimates using the full and the selective sample, IAB employment subsample, 1981-1997

	Full Sample		**Selective Sample**	
Variable	**Hazard Ratio**	**(Std. Err.)**	**Hazard Ratio**	**(Std. Err.)**
Female	1.112**	(0.011)	1.127**	(0.035)
Married	1.219**	(0.008)	1.227**	(0.031)
Married female	0.539**	(0.013)	0.583**	(0.022)
Age < 21	1.217**	(0.010)	1.281**	(0.045)
Age 21-25	1.103**	(0.008)	1.141**	(0.029)
Age 31-35	0.985†	(0.009)	1.001†	(0.029)
Age 36-40	1.000	(0.011)	1.002	(0.031)
Age 41-45	1.001	(0.011)	1.011	(0.035)
Age 46-49	0.968*	(0.013)	0.930*	(0.037)
Age 50-53	0.831**	(0.015)	0.823**	(0.037)
Low education	0.883**	(0.009)	0.847**	(0.023)
Higher education	0.792**	(0.020)	0.779**	(0.044)
Low educ. x Sex	0.968*	(0.013)	1.035*	(0.041)
High. educ. x Sex	1.149**	(0.030)	1.120**	(0.089)
Apprenticeship	1.082**	(0.013)	1.136**	(0.045)
Low skilled worker	0.798**	(0.009)	0.845**	(0.023)
White collar worker	0.752**	(0.010)	0.805**	(0.023)
Parttime work	0.806**	(0.016)	0.829**	(0.035)
Agriculture	1.317**	(0.020)	1.333**	(0.092)
Inv. goods industry	0.927**	(0.010)	0.926**	(0.027)
Cons. goods industry	0.925**	(0.011)	1.029**	(0.036)
Construction	1.221**	(0.010)	1.347**	(0.041)
Services	0.984†	(0.009)	1.024†	(0.025)
Tenure in previous job	0.995**	(0.000)	0.994**	(0.000)
Previous recall	0.781**	(0.012)	0.756**	(0.031)
Total unemp. duration	0.995**	(0.000)	0.997**	(0.001)
1983-1987	1.245**	(0.008)	1.252**	(0.033)
1988-1991	1.332**	(0.009)	1.365**	(0.039)
1992-1997	1.085**	(0.009)	1.122**	(0.032)
Unemployment rate	0.967**	(0.001)	0.971**	(0.005)
Log-likelihood	-1,217,399.365		-121,004	
$\chi^2_{(30)}$	18,724.774		1,961.91	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Using the merging scheme with $S_{D_j} = 1$.

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