

ST2_1 Overlapping numerical variables without a benchmark: Integration of administrative sources and survey data through Hidden Markov Models for the production of labour statistics

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1. Introduction

The increased availability of large amount of administrative information at the Italian Institute of Statistics (Istat) makes it necessary to investigate new methodological approaches for the production of estimates, based on combining administrative data with statistical survey data.

Traditionally, administrative data have been used as auxiliary sources of information in different phases of the production process such as sampling, calibration, imputation. Basically, the classical approach, that could be defined *supervised*, relies on the assumption that, at least after some data editing procedures to remove occasional measurement errors, the survey data provide correct measures of the target variables, so that the use of external sources is essentially limited to the reduction of the sampling error. This is because the measures provided by administrative sources usually do not correspond to the target variables. On the other hand, although surveys are designed to meet the statistical requirements, also statistical data could be affected by measurement errors that may seriously compromise the accuracy of the target estimates.

In order to take into account deficiencies in the measurement process of both survey and administrative sources, a more symmetric approach with respect to the available sources can be adopted. A natural strategy, according to this approach, (*unsupervised* approach), is to consider the target variables as latent (unobserved) variables, and to model the measurement processes through the distributions of the observed variables conditional on the latent variables.

In this latent modeling approach it is useful to classify the variables in three groups:

1. variables Y^* representing the “true” target phenomenon. These are the variables that we would observe if data were error free. In general, Y^* are considered latent variables because they are not directly observed.
2. variables Y^g ($g=1,..,G$) representing imperfect measures of the target phenomenon. These variables are the ones actually observed from G different data sources.
3. covariates X^L and X^M associated respectively to the latent variables Y^* and to the measures Y^g through statistical models.

The statistical model is composed of two components specified via the conditional probability distributions:

$$P(Y^* | X^L) \quad (\text{latent model}), \quad (1)$$

$$P(Y^1, ..., Y^G | Y^*, X^M) \quad (\text{measurement model}) \quad (2)$$

From the conditional distributions (1) and (2) one can derive the marginal distribution $P(Y^1, ..., Y^G | X^L, X^M)$ of the imperfect measures:

$$P(Y^1, ..., Y^G | X^L, X^M) = \int P(Y^1, ..., Y^G | Y^*, X^M) P(Y^* | X^L) dY^*$$

Then, model parameters can be estimated using a likelihood approach, based on the data observed from the G different sources. Once the model parameters have been estimated, we can derive the marginal distributions $P(Y^g | Y^*, X^M)$, $g = 1, \dots, G$ from (2). These distributions can be used to assess the accuracy of each source and the sources can be ranked accordingly. Using Bayes theorem one can derive the distribution of the latent variables conditional on the available information (*posterior distribution*):

$$P(Y^* | Y^1, \dots, Y^G, X^M, X^L)$$

And use the expectations from this distribution to obtain predictions of the true values for each unit.

2. Use of administrative and statistical data for labour statistics

The main sources available for the production of labour statistics are the Italian Labour Force Survey (LFS) and administrative sources mainly providing social security and fiscal data.

The Italian LFS is a continuous survey carried out during every week of the year. Each quarter, the LFS collects information on almost 70,000 households in 1,246 Italian municipalities for a total of 175,000 individuals. The LFS provides quarterly estimates of the main aggregates of labour market (employment status, type of work, work experience, job search, etc.), disaggregated by gender, age and territory (up to regional detail).

Administrative data relevant for the labour statistics come mainly from social security, Chambers of Commerce and fiscal authority. Data are organized in an information system having a linked employer-employees (LEED) structure. From this data structure it is possible to obtain information on the statistical unit of interest, i.e., the worker. The main goal of this analysis is twofold: 1) to produce statistics on the employment status by small geographical domains in order to fulfill the population census requirements; 2) to improve the accuracy of the labour force estimates.

Within the general framework described above appropriate models are Hidden Markov Models (HMM). In fact the methodological choices have to take into account that the variable of interest is categorical and the data are longitudinal.

According to the HMM modeling, the latent variable at time t , S_t takes values on a finite set of size r that we can identify, without loss of generality, with the set $(1, 2, \dots, r)$. For a given final time T , the values $(s_0, s_1, s_2, \dots, s_T)$ represent the realization of an unobserved random process S at discrete times $0, 1, \dots, T$. We assume that the stochastic process S is a first order Markov process, that is $P(S_{t+1} | S_1, S_2, \dots, S_t) = P(S_{t+1} | S_t)$. The law of this process is specified through the *initial probabilities* $p_j^0 = P(S_0=j)$ ($j=1, \dots, r$), and the *transition probabilities* $p_{ji}^t = P(S_{t+1}=j | S_t=i)$ ($i, j=1, \dots, r$; $t=1, \dots, T$).

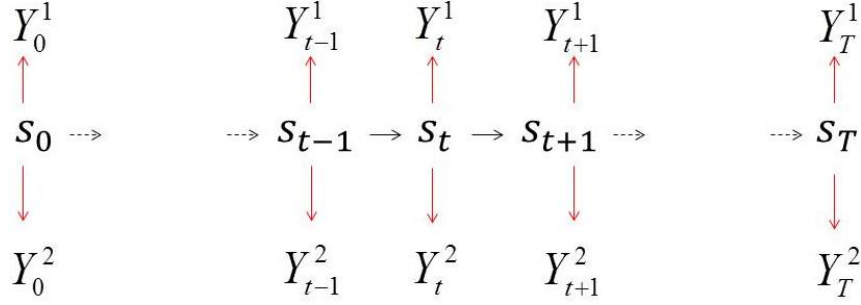
Furthermore, we assume that, at each time t , a set of G imperfect measures Y_t^g ($g=1, \dots, G$) is also available. If we consider the manifest variables Y_t^g as measures with error of the target variable S_t , it is natural to assume that they take values on the same set $(1, 2, \dots, r)$ associated with the categories of S_t . However, in some circumstances it is useful to allow for more general situations where the latent process and the manifest variables take values on different domains. For instance, this is the case if S_t take values 1=*employed*, 2=*unemployed*, 3=*economically inactive*, while the categories of Y_t^g are only *employed* (1) and *not employed* (2+3).

In the basic version, the measurement process is modeled by assuming *local independence* among the manifest variables:

$$P(Y_t^1, \dots, Y_t^G | S_t = s_t) = \prod_{g=1}^G P(Y_t^g | S_t = s_t). \quad (3)$$

The meaning of the equation (3) is that the G measures Y_t^g are conditionally independent, given the true value of the target variable S_t (see Figure 1 for a graphical representation of the conditional independence structure of the HMM in the case $G=2$).

Figure 1. Hidden Markov Model with $G=2$ data sources.



Estimates of the model parameters can be obtained via likelihood methods provided that the model is identifiable. The latter condition is trivially not valid if the number of parameters to be estimated is higher than the numbers of distinct combinations of values of the observed variables.

In cases where there exists a one-to-one relation between the categories of the variable Y_t^g and the state of the latent process S , the (estimates of the) probabilities $\psi_{ji}^g \equiv P(Y_t^g = j | S_t = i)$ can be used to evaluate the accuracy of the measurement process associated to the source g .

The methodology can be easily extended by introducing covariates in the latent process as well as in the measurement model. This is usually done by relating the involved probabilities to the covariates through multinomial-logit models. Moreover, mixtures of HMMs can be used in order to account for possible heterogeneity among the units of the population.

If the latent model is not only used to assess the quality of the available sources, but also to directly provide estimates of some finite population quantities, one can use the Bayes formula to derive the posterior probabilities of the true target variable conditional on the available information (manifest variable and covariates). Specifically, given G sequences $Y_{k,1:T}^g \equiv (Y_{k1}^g, \dots, Y_{kT}^g)$ of values of the manifest variables and values of the covariates $X = (X^L, X^M)$ for each unit k of the population, the relevant probability distribution is:

$$P(s_{k1}, \dots, s_{kT} | Y_{k,1:T}^1, \dots, Y_{k,1:T}^G; X^L, X^M). \quad (4)$$

Different usages of distribution (4) are possible. For instance, estimates of linear aggregates referring to time t can be obtained by taking expectations from the conditional distribution $P(s_{it} | Y_{i,1:T}^1, \dots, Y_{i,1:T}^G; X^L, X^M)$, resulting by marginalization of (4). Furthermore in a general purpose estimation context, one can build a synthetic micro-data file by random drawing from distribution (4).

3. Experimental study

In this section, we illustrate a simulation study where the methodology described above is applied in different scenarios. The main goal of the study is to assess the robustness of the methodology with respect to departure from the model assumptions. In particular, we are interested in evaluating the robustness of the measurement error parameter estimates and of the aggregate estimates based on prediction of the latent variable given the observed measurements.

In all scenarios, N arrays of T binary values are drawn from a discrete time process which is assumed to be the latent process. The t component of the i th array S_{it} ($i=1,..,N$; $t=1,..,T$) represents the true employment status of the i th individual at time t in a population of size N . Since according to the international regulation, the reference time for the employment status is the week, we set $T=52$ which is the number of weeks in a year.

For each individual and each time, two different imperfect measures (Y_{it}^A, Y_{it}^L) of the latent process are also simulated by independently drawing two binary values at each time, conditionally on the realized values of the latent process. In other words, given a realization of the latent variable S_{it} , we draw the two imperfect measures Y_{it}^A, Y_{it}^L from the conditional distribution $P(Y_{it}^A, Y_{it}^L | S_{it} = s_{it}) = P(Y_{it}^A | S_{it} = s_{it})P(Y_{it}^L | S_{it} = s_{it})$.

In order to mimic the real scenario where one of the sources (labour force survey) is available only on a sample of size n , we assume that the measure Y^L is observed only on n units. For the sake of simplicity, we do not take into account the labor force sampling design and we draw the n sample units according to a simple random sampling.

Moreover, in order to reproduce the missing pattern of the labour force survey implied by the sample design, we drop values in the Y^L source so that for each individual i , the corresponding measure is available not more than twice in the year and not more than once in a quarter.

In the following, several simulation scenarios are described differing for the distribution generating both the “true” data and the manifest measures. For each scenario we try to fit data through some latent models and we obtain the model parameters estimates via maximum likelihood estimation. We split data in two datasets E and P : E is used to estimate the model while P is used as test set. Specifically, given the parameter estimates obtained from E , these estimates are used to predict values of the latent variables at different times conditionally on the available information. Evaluation is performed by comparing the estimates of the annual averages of “employed” based on predictions with the corresponding number of true “employed”. Moreover, in order to evaluate the capability of the method to correctly assess the quality of the different sources of information, the estimates of the parameters associated with the measurement processes (classification errors) are also compared with the corresponding true values.

For the conditional distributions associated with the measurement processes we will use the following notation:

$$\psi_{k|j}^L \equiv P(Y_{it}^L = k | S_{it} = j), \psi_{k|j}^A \equiv P(Y_{it}^A = k | S_{it} = j); \quad i = 1,.., n; \quad j, k \in (0,1); \quad t = 1,.., T$$

While initial probabilities and transition probabilities from state i , to state j will be denoted by p_i^0 and $p_{ji} = P(S_{t+1}=j | S_t=i)$ respectively. Note that, since the latent processes are supposed to be time homogeneous in all scenarios, dependence on time has been removed from the notation.

A Monte Carlo simulation study is carried on considering three different scenarios. In all scenarios, $R=100$ replications have been simulated. For each replication $N=1000$ binary arrays with $T=52$ time occasions and two imperfect measures are drawn. In the following, the different simulation scenarios (S1-S3) are described.

S1) In this scenario we simulate the latent process as a two state Markov chain with 52 time occasions and the two measurement processes through the specification of the corresponding conditional distributions.

Two experiments SI_a and SI_b are conducted differing for the set of parameters of the measurement process:

$$SI_a : \psi_{1|0}^L = 0.05, \psi_{0|1}^L = 0.1; \psi_{1|0}^A = 0.2, \psi_{0|1}^A = 0.1$$

$$SI_b : \psi_{1|0}^L = 0.4, \psi_{0|1}^L = 0; \psi_{1|0}^A = 0.2, \psi_{0|1}^A = 0.1$$

The second set of parameters corresponds to situations where one of the two sources measures the target variable correctly when the true value is equal to one, while the probability of misclassification is high when the true value is zero.

The probability at $t=0$ and the independent parameters of the transition matrices are in both cases:

$$p_{01} = 0.4, p_{1|0} = 0.07, p_{0|1} = 0.05$$

For each set of parameters we estimate two models corresponding to different choices of the reference time for the dynamic of the employment status. Specifically, in the first case, we suppose, according to the simulation model, that the reference time for the Markov chain is the week (52 times). In the second model, we synthetize the weekly available information at month level by considering only one value per month of the manifest variables (12 times). In detail, for each month of the year we take for Y^L (representing the labour force survey) the unique available value (when present) as representative of the month. The week representing Y^A in the month is the same as Y^L when it is present, and is randomly selected otherwise. Collapsing information from week level to month level could be an option for dimensionality reduction. Thus, we performed this experiment in order to analyze the impact of the approximation on the accuracy of the estimates.

The main goal of the other experiments is to investigate robustness of the methodology with respect to misspecification of the underlying model.

S2) In this scenario we simulate the latent process as a mixture of two Markov chains $C1$ and $C2$ with probabilities at $t=0$ and transition parameters $p_{j|i}^1$ and $p_{j|i}^2$ given by:

$$p_{01}^{01} = 0.6 \text{ and } p_{01}^{01} = 0.5; P_{1|0}^1 = 0.07, p_{0|1}^1 = 0.05; p_{1|0}^2 = 0.3, p_{0|1}^2 = 0.4.$$

The mixing weight of the mixture is $\pi = 0.7$

The measurement processes are simulated according to the following values of the probabilities for the classification errors:

$$\psi_{1|0}^L = 0.05, \psi_{0|1}^L = 0.1; \psi_{1|0}^A = 0.2, \psi_{0|1}^A = 0.1$$

The scenario represents situations where individuals can be classified in two groups with different characteristics in terms of employment dynamics. Total employment and classification errors are estimated by modeling data both with a simple HMM (basic model) and with the appropriate mixture of HMMs (mix model).

S3) In the last group of experiments we simulate heterogeneity among the units by allowing that the initial probabilities and transition matrix to depend on a set of four binary covariates X_1, \dots, X_4 . Dependence is modeled through logit functions. The measurement processes are simulated according to the following values of the probabilities for the classification errors:

$$\psi_{1|0}^L = 0.05, \psi_{0|1}^L = 0.1; \psi_{1|0}^A = 0.2, \psi_{0|1}^A = 0.1$$

We obtain predictions and estimates of the classification errors using 4 models:

- 1) A simple HMM (basic)
- 2) A two component mixture of HMMs (mix2)
- 3) A three component mixture of HMMs (mix3)
- 4) The appropriate HMM where covariates for the latent process are correctly specified (cov).

Bias and RMSE (Root Mean Squared Error) for the estimation of the parameters of the measurement processes are reported in Table 1. Figures 1-3 show the distributions of the estimation errors, respectively for scenarios *S1-S3*.

Table1. Bias and RMSE for the estimates of the parameters of the measurement processes

Simulated Model	Estimated model	BIAS				RMSE			
		$\psi_{0 1}^A$	$\psi_{1 0}^A$	$\psi_{0 1}^L$	$\psi_{1 0}^L$	$\psi_{0 1}^A$	$\psi_{1 0}^A$	$\psi_{0 1}^L$	$\psi_{1 0}^L$
<i>S1a scenario</i>	<i>Basic 52 weeks</i>	-0.0007	0.0003	-0.0010	-0.0007	0.0050	0.0034	0.0174	0.0114
	<i>Basic 12 months</i>	0.0081	-0.0014	-0.0049	-0.0039	0.0677	0.0145	0.0302	0.0192
<i>S1b scenario</i>	<i>Basic 52 weeks</i>	0.0001	-0.0003	0.0009	-0.0028	0.0048	0.0035	0.0025	0.0235
	<i>Basic 12 months</i>	-0.0022	-0.0063	0.0044	-0.0039	0.0216	0.0136	0.0084	0.0261
<i>S2 scenario</i>	<i>Basic</i>	0.0581	0.0102	0.0354	-0.0041	0.0588	0.0112	0.0414	0.0148
	<i>Mixture 2 comp</i>	0.0220	0.0242	0.0242	0.0170	0.0927	0.0874	0.1318	0.0794
<i>S3 scenario</i>	<i>Basic</i>	0.0272	0.0197	0.0007	0.0020	0.0544	0.0231	0.0371	0.0532
	<i>Mixture 2 comp</i>	0.0087	0.0051	0.0028	0.0006	0.0502	0.0159	0.0364	0.0546
	<i>Mixture 3 comp</i>	0.0029	0.0015	0.0047	0.0010	0.0501	0.0142	0.0374	0.0544
	<i>Covariates</i>	-0.0006	-0.0013	0.0085	0.0057	0.0220	0.0149	0.0376	0.0351

Table 1 shows that the estimates of the parameters $\psi_{j|i}^A$ and $\psi_{j|i}^L$ are not biased in all scenarios. The accuracy level seems quite high in all cases except for the scenario *S2* where in some cases the RMSE is around 10%. In particular, the results for scenarios *S1a* and *S1b* show that, as expected, the accuracy level decreases as we move from the weekly reference period to the monthly reference period. Moreover, different sets of parameters in the simulated model do not seem to imply significant change of the accuracy level. All these findings are confirmed in Figure 1. It is worthwhile noting that when the true error parameter $\psi_{0|1}^L$ is equal to zero the corresponding estimation error vanishes.

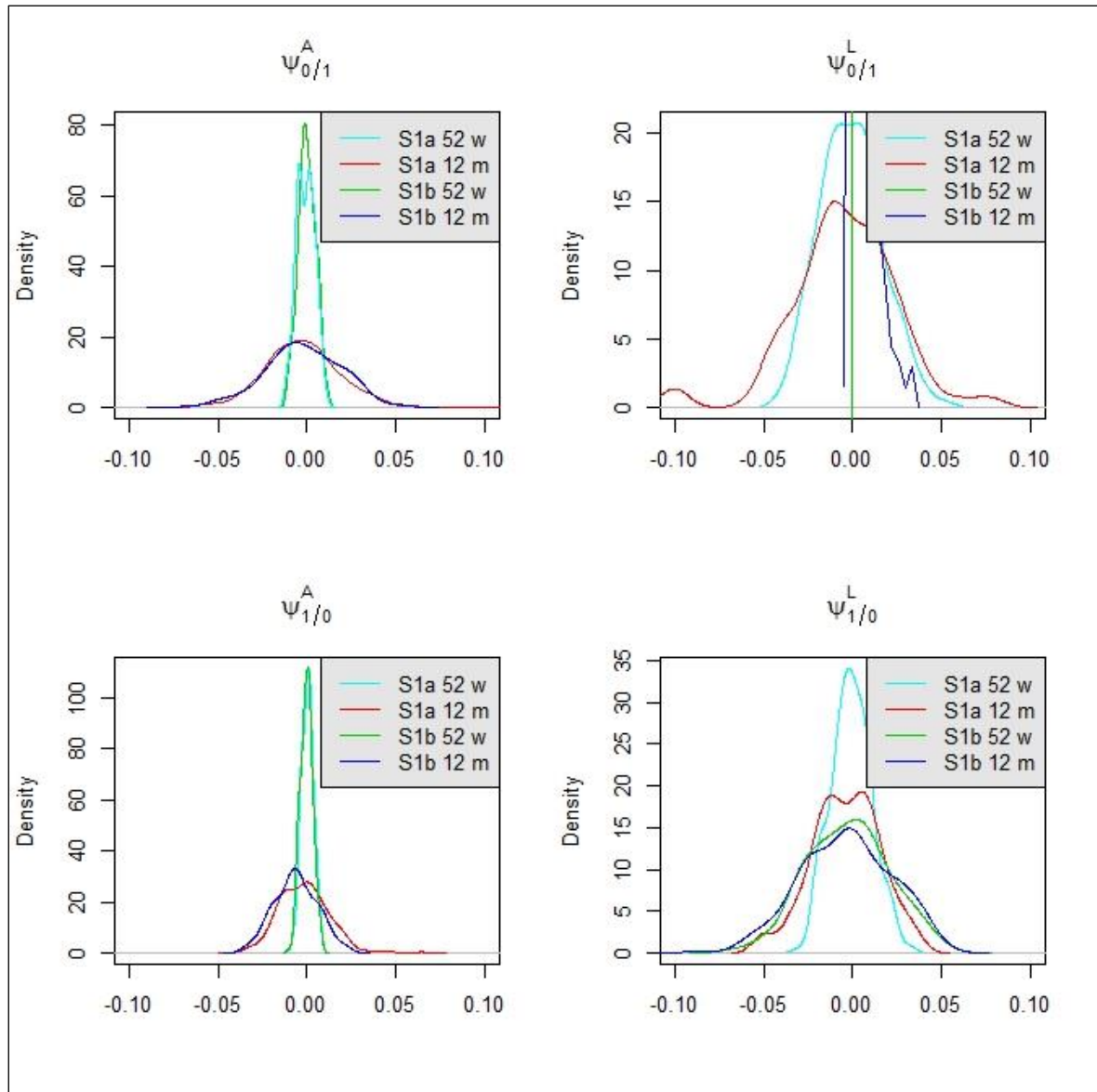


Figure 1. Distributions of the estimation errors for the parameters of the measurement processes - scenarios S1a and S1b

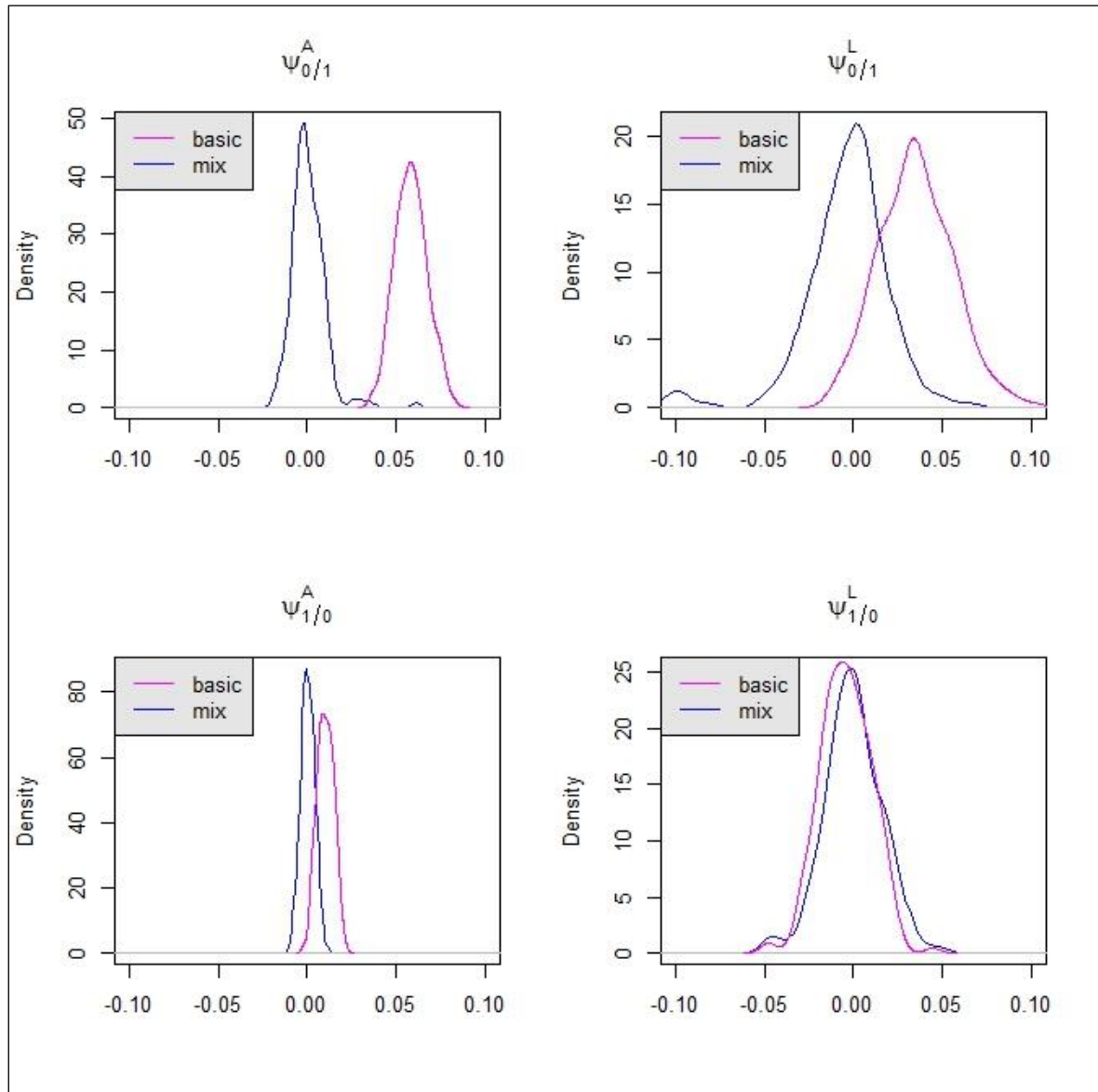


Figure 2 Distributions of the estimation errors for the parameters of the measurement processes - scenario S2

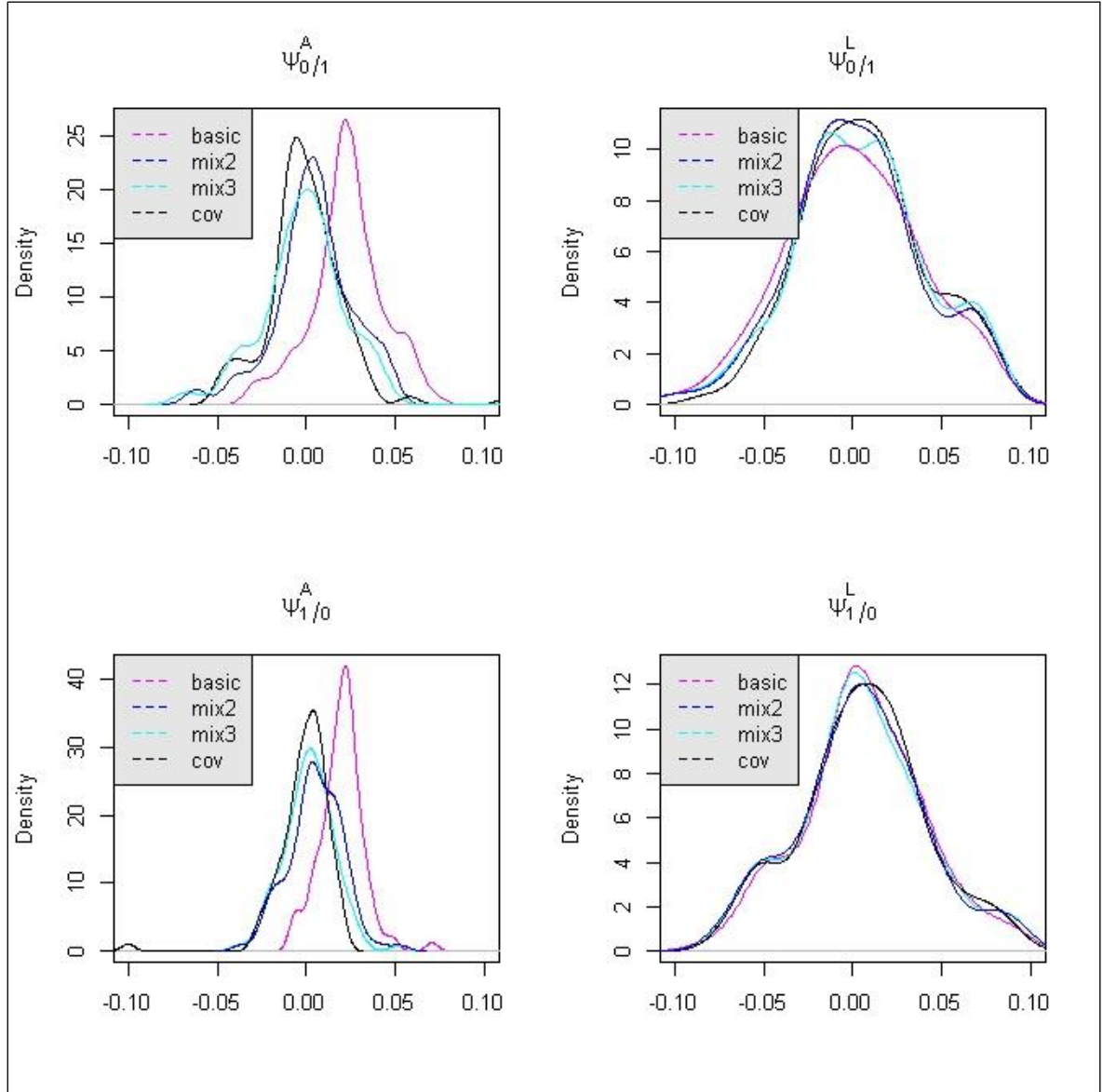
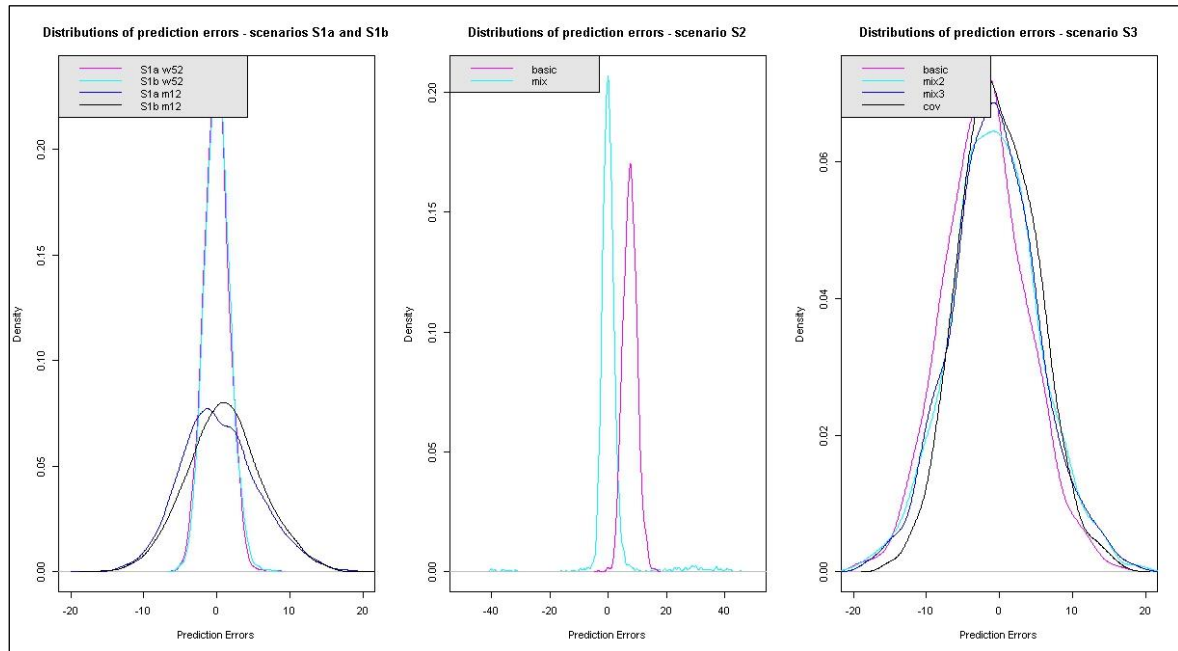


Figure 3. Distributions of the estimation errors for the parameters of the measurement processes - scenario S3

As far as the robustness of the estimation method is concerned, we notice that when we simulate true data from mixture of HMMs, or HMM with covariates (scenarios *S2* and *S3*), the estimates obtained via the basic HMM in most cases are biased. It is also interesting to note that the accuracy level of the error parameters is lower for the measure with a high rate of missing values (ψ^L).

Table2. BIAS and RMSE for the prediction errors

Simulated Model	Estimated model	Prediction errors	
		BIAS	RMSE
<i>S1a scenario</i>	<i>Basic 52 weeks</i>	-0.0628	1.6978
	<i>Basic 12 months</i>	0.3714	5.2928
<i>S1b scenario</i>	<i>Basic 52 weeks</i>	-0.0621	4.0159
	<i>Basic 12 months</i>	0.2215	9.4780
<i>S2 scenario</i>	<i>Basic</i>	7.5007	7.8658
	<i>Mixture 2 comp</i>	0.7219	6.2633
<i>S3 scenario</i>	<i>Basic</i>	-1.3861	4.7556
	<i>Mixture 2 comp</i>	-0.4677	4.7199
	<i>Mixture 3 comp</i>	-0.5599	4.6703
	<i>Covariates</i>	-0.2059	4.5738

**Figure 4 Distributions of the prediction errors in scenarios S1-S3**

The results in Table 2 and Figure 4 concerning the distributions of prediction errors agree with the previous findings. In particular, the accuracy level of the predictions is definitely lower when moving from week to month for the reference time. Furthermore, in presence of heterogeneity among individuals (scenarios S2 and S3), the basic model provides strongly biased estimates whereas the mixture of HMMs seems to approximate quite well the true data distribution.

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ST2_2 Overlapping numerical variables with a benchmark

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Data configuration ISTAT has also examined basic data configuration 2 for the situation where there are overlapping units as well as overlapping variables in the data sources to be combined and one of the data sources (typically a survey measure) is considered as error free and the administrative measures are merely used as auxiliary information.

Thus, differently from the situation in Istat Suitability test n.1, the error free variable (Y) is modelled as a *response* variable and all the other measures (X) are considered *covariates*. This supervised approach can be adopted in a model based inference as well as in a design based inference. In the latter case, the covariates can be used to specify a *working* model (model assisted approach). The choice of the methodological approach depends both on the informative content and the quality of the available data sources.

In this situation, where administrative data play the role of auxiliary variables, evaluation of accuracy is primary based on the estimation of sampling error.

If we assume that administrative and survey data have an asymmetric role, then adequate statistical models can be applied only to the units belonging to survey samples and the corresponding estimates can then be used to predict the phenomena over the unsampled population units, either using a model-based (not considering sample weights) or a design-based approach (considering information deriving from the survey sampling scheme).

The choice of a projection unit level estimator is connected with (i) the purpose of producing a microdata archive which can be used to spread information at the required territorial levels, such as municipal level and (ii) and the need to produce coherent estimates with those provided by different ISTAT surveys dealing with the same thematic areas of interest (employment area in this case).

Also in this setting one can use the employment status provided by the Labour Force Survey (LFS), which provides the target variable that need to be estimated, and the administrative data as auxiliary determinants in estimating the phenomena of interest.

Different options for the estimator will be tested. The first is the model assisted linear estimator proposed by Kim and Rao (2012). Other estimators are the composite estimator deriving from the linear mixed model where the random effects are the Labour Market Areas (LMAs).

Data used Again the goal of the study is to combine administrative and survey data in order to build a “labour register” to be used for producing estimates on the employment status at fine level. To this aim, data from the Italian Labour Force Survey (LFS) and administrative data strongly associated with the target phenomenon are used. The experimental study is conducted on data coming from the Italian regions Trentino-Alto Adige and Marche.

Results In order to analyse the feasibility of the application of a projection estimator to employment LFS data considering as auxiliary variables administrative information already mentioned before, with the aim to produce different territorial levels estimates (provinces, macro LMAs, LMAs and municipalities) a simulation scheme has been implemented. This simulation scheme consists of drawing different samples,

estimating the model over the samples and projecting the results over the entire population. The performance is assessed in terms of bias and mean squared errors by means of:

$$MARE = \frac{1}{D} \sum_{d=1}^D \left| \frac{1}{R} \sum_{r=1}^R \hat{y}_{rd} - Y_d \right|, \text{ARRMSE} = \frac{1}{D} \sum_{d=1}^D \frac{1}{R} \sqrt{\frac{\sum_{r=1}^R (\hat{y}_{rd} - Y_d)^2}{Y_d}}$$

The following model specifications have been used in the experimental study.

Projection on pooled sample

Full model: Marital status, educational level, citizenship, not in labour force, cross classification gender-age, register variable by region

Reduced model: Marital status, educational level, citizenship, cross classification gender-age, register variable by region

Projection on register

Minimal model: Marital status, citizenship, cross classification gender-age, register variable by region

The main results in terms of bias and mean squared errors for the target variables employment status and unemployment status are given in Tables 1 and 2 below.

Table 1. MARE and ARRMSE for the variable employment status

	GREG LFS	Projection LFS on Pooled Reduced model	Projection LFS on Pooled Full model	Projection LFS on Register Minimal model	Projection Pooled on Register Minimal model	Pooled	EBLUP
Mean Absolute Relative Error - Employed							
R²	-	0.89	0.95	0.89	0.89	-	-
Province (7)	0.33	0.55	0.56	0.12	0.08	0.60	-
Macro LMA (14)	1.97	0.47	0.49	0.14	0.09	0.44	2.42
LMA (54)	232.12	73.32	74.04	1.15	1.11	72.32	2.74
Municipality (527)	1779.27	550.48	550.09	1.97	1.96	551.12	3.48
Average Relative Root Mean Squared Error - Employed							
Province (7)	4.126	5.52	5.49	1.51	0.95	5.4	-
Macro LMA (14)	21.36	3.15	2.96	2.07	1.31	2.73	3.74
LMA (54)	264.32	109.25	110.96	2.60	1.91	108.25	4.08
Municipality (527)	1791.43	608.87	608.87	3.10	2.52	610.36	4.62

Table 2. MARE and ARRMSE for the variable unemployment status

	GREG LFS	Projection LFS- Pooled Reduced model	Projection LFS- Pooled Full model	Projection LSF- Register Minimal model	Projection Pooled-Register Minimal model	Pooled	EBLUP
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Mean Absolute Relative Error - Unemployed							
R^2	-	0.15	0.33	0.15	0.14	-	-
Province (7)	0.88	1.04	2.12	0.96	0.46	0.61	-
Macro LMA (14)	2.53	1.25	1.40	1.36	1.05	0.98	34.19
LMA (54)	243.45	68.22	44.52	12.32	12.78	82.3	49.28
LMA in-sample (26)	8.06	7.23	6.28	5.25	5.22	2.78	36.55
Average Relative Root Mean Squared Error - Unemployed							
Province (7)	16.12	15.56	15.01	14.55	9.33	12.78	-
Macro LMA (14)	30.65	22.52	22.21	22.12	14.37	15.85	42.82
LMA (54)	312.93	111.71	99.37	29.08	21.09	136.72	57.45
LMA in-sample (26)	54.58	34.63	34.54	22.22	15.83	33.11	44.37

Analysis of results

The results for the variable *employed* are shown in Table 1 in which the R^2 shows very high values for all the models. The MARE and the ARRMSSE indicators are computed for the four type of domains described above. At province level the best results are obtained by the Projection estimator using the register, but also good performances are obtained for direct GREG estimator. At Macro-LMA level the GREG estimator loose its good properties showed at provinces level, presenting a huge increase of variability (ARRMSSE 21.36%). The Pooled estimators presents still good results on this level, very closed to the Projection estimator using the register. At LMA and at municipality level the estimators both based on the LF data or on the pooled sample show very poor results with respect to those referred to macro-LMA. This is due to the fact that on 54 LMA areas included in the regions only 26 are always present in the 200 simulations, while for the municipalities on 572 areas only 27 are always included in the simulations. For this reason, the synthetic estimators (projection on register and SAE estimator) show similar results in terms of bias and variability as well.

The results for the variable *unemployed* are shown in Table 2. For this variable the R^2 value is similar using the *reduced* and the *minimal* model (14-15%) while goes up to the 33% using the *full* model. As well as for the employed, at provinces level and at Macro-LMA good results are obtained from the GREG estimator and from the Pooled estimator, especially in terms of bias. At LMA level only the projection on register estimator show good performance both with the MARE and the ARRMSSE indicators below the threshold of the 13% and the 30%. The table 3 shows that considering only the 26 LMAs always sampled in the 200 simulations, the bias estimates goes down up to the 5%.

Gap analysis: A very useful aspect to be accounted for in the employment status estimation at a certain time t , is the one relying to the individual previous times employment status information. Considering the longitudinal aspect is not always trivial. An interesting research topic we propose to develop in the future is inherent to the utilization of longitudinal models in case of not balanced samples and in a projection model-assisted approach for micro data. This would make the developed approach more generally applicable.

References

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