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HOW "REAL" IS MOBILITY FROM TEMPORARY TO PERMANENT EMPLOYMENT IN ITALY? A FOCUS ON MEASUREMENT ERROR

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Abstract *The aim of this paper is to study the effect of measurement error on mobility between different employment types in Italy. For this purpose, we apply a hidden Markov model with two independent indicators for the employment category (permanent contract, temporary contract, self-employed, not employed). The model takes into account that both sources may not be error-free as well as that measurement error may be correlated over time. The two indicators come from ISTAT administrative data and the Labour Force Survey from 2017 to 2021, linked at the individual level. The results show that neither source can be considered error-free and that measurement error severely biases mobility between employment states.*

Keywords: *Hidden Markov model Latent variable model Multi-source data Employment career Measurement error.*

1. INTRODUCTION

In the last decades, flexible employment has been at the centre of political and scientific debate in Europe. In the countries of the Eurozone, in 2021, 11.4% of all individuals in paid employment were employed with a temporary contract (OECD, 2023). Latner (2022) found that, over time, while the temporary employment rates stagnated, the risk of temporary employment increased. In more detail, following a period of growth (1996-2007), the incidence of temporary employment remained stable in Europe between 2007 and 2019. However, between

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2013 and 2019, the risk of experiencing at least one temporary employment contract increased by 36%. Italy presents an exceptional case in Europe as it is one of the few countries where both the incidence and the risk of temporary employment increased. Specifically, between 2008 and 2019, the incidence of temporary employment increased from 11.4% to 16.4% (OECD, 2023), while the risk of temporary employment from 14.9% to 22.7% (Latner, 2022). Research has also shifted its focus from the incidence of temporary employment to mobility in and out of temporary employment instead. The reason is that, although there is consensus that ceteris paribus, temporary employment is inferior to permanent employment (Amuedo-Dorantes and Serrano-Padial, 2007; Gash and McGinnity, 2007; Gebel, 2010; Mooi-Reci and Dekker, 2015; Pavlopoulos, 2013), there is still debate on the role of temporary employment in the life course. In this, two very different scenarios exist: temporary contracts sometimes serve as a stepping-stone to a permanent job, while other times can lead to a trap of precarious jobs and unemployment (Latner and Saks, 2022). To determine which of the two scenarios prevail, we need reliable estimates of the transition rate from temporary to permanent employment.

As shown by Pavlopoulos and Vermunt (2015), findings on mobility from non-permanent to permanent employment can be biased due to measurement error, usually present in the data used for analysis. In survey data, measurement error is the result of problems related to cognitive processes, social desirability, design and implementation (Groves, 2004; Sudman et al., 2004; Tourangeau et al., 2000). In register/administrative data, measurement error is the result of administrative delays, misregistration or faulty administrative procedures (Bakker and Daas, 2012; Oberski, 2017). This measurement error may be either random or systematic. Systematic error may come in surveys, e.g. due to dependent interviewing, and in registers due to administrative procedures (e.g. when firms report information retrospectively to the Employment Office). Pavlopoulos and Vermunt (2015) find, by employing a hidden Markov model, that random and systematic errors in the Labour Force Survey and the Dutch Employment Register of the Netherlands considerably bias our view for mobility from temporary to permanent employment in the Netherlands. These findings are confirmed by Pankowska et al. (2018, 2021).

In this paper, we build on the approach of Pavlopoulos and Vermunt (2015) and utilize a hidden Markov model to estimate and correct for measurement error in employment mobility in Italy. For this purpose, we use a unique dataset with linked information from the Labour Force Survey (LFS) and administrative data

(AD) provided by the Italian National Institute of Statistics (Istat). Specifically, we aim to determine the "true" size of temporary employment and the "true" transition rate from temporary to permanent employment in Italy. Our analysis spans the years 2017 to 2021. The modeling approach we employ, HMms, offers flexibility, allowing us to refrain from considering any of the data sources as error-free (i.e. "gold standard"). Instead, it enables us to estimate and correct measurement errors within each source. Furthermore, the use of multiple indicators for the phenomenon of interest, namely employment status, enables us to model realistic specifications for measurement errors. This encompasses both random and systematic errors, as discussed in Biemer (2011) and Vermunt (2010).

The rest of the paper is organized as follows. In Sections 2 and 3 we present the data and the HMm, respectively. In Section 4 we describe the results of the analysis and in Section 5 we discuss the conclusions of our research.

2. THE DATA

The Italian National Statistical Institute, Istat, relies on multiple data sources to gather information on employment. The primary source for official labour market statistics is the LFS, which is directly administered by Istat. Additionally, Istat gathers and processes data from various administrative sources as part of its routine operations to provide statistical information on various aspects of the labour market.

The Italian LFS follows the standards set by EU Regulation 2019/1700 of the European Parliament and the Council. The survey is conducted throughout the year and covers approximately 1.2% of the entire Italian population. Each year, it involves approximately 250,000 households and 600,000 individuals residing in Italy, distributed across roughly 1,400 Italian municipalities. The Italian LFS operates on a rotating quarterly scheme. Selected households are interviewed four times within a 15-month period. Each household is interviewed for two consecutive quarters, followed by a two-quarter break and another two consecutive survey quarters. Interviews are spread across all weeks of the quarter. Data collection utilizes a combination of computer-assisted personal interviews and telephone interviews. The information that is collected refers to the time of the interview. For further details on the LFS contents, methodologies and organization see Istat (2006). Italian AD pertinent to labour statistics are collected by social security and tax authorities. Social security authorities release different data sources depending on the type of employment contract, while tax authorities release different data sources depending on the tax deadline. It is important to note that the quality of information differs considerably between administrative sources. Therefore, these data go through different, source-specific editing and harmonization procedures (Baldi et al., 2018; Istat, 2015). Harmonized data is organized within an information system featuring an employer-employee linkage structure. This structure serves as the foundation for extracting information regarding the primary unit of analysis, the "worker". Specifically, for each individual, the primary regular job and its associated characteristics are determined according to the definitions outlined by the International Labour Office, guiding also the classification criteria used also by LFS. Additionally, the treatment of data varies according to the type of employment relationship, i.e. whether this relationship involves self-employment, paid employment, or work as a dependent contractor.

We use linked quarterly data from the LFS and AD for the period from 2017 to 2021. The linkage between the two datasets was conducted at the individual level utilizing an internal statistical code, which facilitates the integration of diverse data sources within the Italian National Statistical Institute. To cope with the growing volume of administrative datasets acquired for statistical analysis, Istat has developed the Integrated System of Microdata (SIM). This system centralizes functions such as data acquisition, storage, integration, and assessment of administrative data quality. The integration process within SIM entails linking and harmonizing microdata sourced from different external data sources in addition to surveys. Tailored integration strategies and algorithms are deployed depending on the available linking variables, ensuring consistent and high-quality data integration (Runci et al., 2018).

The above-mentioned process of linking the LFS and AD results in a total of 20 data points per individual. From the LFS, information from all survey waves in which these individuals participated is retained. The actual number of LFS observations in the data may be less than 4 in case of attrition or in cases where the LFS rotation scheme commenced before 2017 or ended after 2021. For the same set of individuals, quarterly information from the AD is retained, covering all quarters from January 2017 to December 2021. For each individual, there is a maximum of four observations from the LFS, whereas the AD dataset contains no missing data. We include in our data individuals aged 25 to 55 who participated at least once in the LFS within this period. By excluding young workers who frequently exhibit significant mobility and often combine employment alongside education, as well as older workers who are in the preparatory phase for retirement transition, we ensure a more homogeneous population. As our statistical model is computationally demanding, a 10% sample of units was randomly selected.

To ensure that overlap between the LFS and AD is retained for all time points, we stratified the sample by the month of the first LFS interview. This procedure resulted in a sample of 39,847 individuals. A random sample was necessary as the analysis is computationally infeasible with the full sample in any available software. A consequence of this is that the original sample weights are no longer valid; to include sampling weights, we would need to derive new ones, but this extends beyond the scope of this project. Further, as the sampling weights are related to demographic characteristics but are unrelated to the outcome variables of interest, using these weights would not affect the parameters of interest in the model.

From the LFS, we derive information on employment status, the type of employment contract, the number of hours worked during the reference week, and educational level. In addition, we have information on whether the interview was conducted by the individual or by a proxy[2]. From AD, we retain information on the employment status, the type of employment contract, age, gender, citizenship, municipality of residence, and labour income classified into various income classes.

The breakdown of the workforce based on their Status in Employment is fundamental in labour statistics, as comprehending transitions among different employment categories is essential for thoroughly understanding a country's labour market dynamics. The International Classification of Status in Employment (ICSE-18), established by the International Labour Organization (ILO), comprises 10 distinct categories of Status in Employment, with the aim of providing a detailed classification that reflects the various working relationships within the labour market. Recognizing the challenge presented by managing these 10 categories, both in terms of classification and statistical dimension, we aggregate them into three main groups: (1) employees with a permanent contract (PE), (2) employees with a temporary contract (FT), and (3) self-employed (SE), which encompasses Employers, Independent workers without employees, Contributing family workers, and dependent contractors. Additionally, our classification includes those who are not employed (NE). The development of this simplified classification is relatively straightforward for LFS data, given that ICSE has been implemented in the LFS and builds upon the prevalent practice of using self-identification questions. Specifically, for the Italian LFS, we utilize questions related to the Status

[2]LFS is a household survey. This means that every time one household member provides information for all (relevant) members of the household. This means that for some individuals, information is provided by a different member of the household, a proxy.

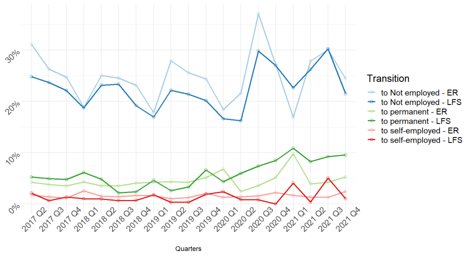
in Employment in the main job and the Permanency of the main job. However, deriving the Status in Employment from administrative data poses challenges and remains an ongoing subject of discussion within statistical offices. Additionally, the derivation process varies across European countries and is contingent upon the types of available administrative sources. In Italian AD, employees can be identified through social security data, with further categorization into permanent or temporary based on administrative contract types. Self-employed individuals are identified by integrating various sources such as social security data, fiscal data, and the business register. It is important to note that the administrative classification may not fully align with the self-reported classification in the LFS, as it is based on administrative concepts. Additional conceptual discrepancies between LFS and AD can be attributed to shortcomings in the data collection process. These include e.g. temporal misalignment of sources, particularly for occasional employment, a structural absence of administrative details regarding irregular work, discrepancies in the definition of employment across available sources. Tables 1 and 2 display the transition rates between the different employment catagories in adjacent quarters in the LFS and AD. The disparities between the two transition matrices are relatively minor.

Table 1: Observed transitions in LFS. Years 2017-2021

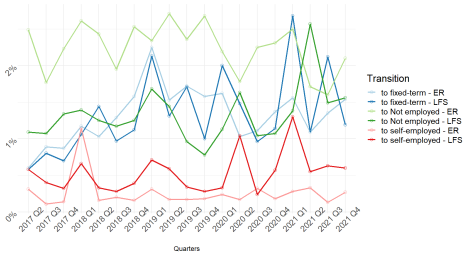
Employment category $t-1$	**Employment category t**			
	PE	**FT**	**SE**	**NE**
Permanent contract	0.962	0.012	0.006	0.020
Temporary contract	0.074	0.739	0.013	0.174
Self-employed	0.015	0.010	0.944	0.031
Not employed	0.019	0.063	0.013	0.906

Figures 1 shows the observed transition rates between different contract categories across adjacent quarters from 2017 to 2021. These transition rates are derived from LFS data and ER. In the case of LFS data, transitions are considered only when there are consecutive observations available. Specifically, Figure a) illustrates the transition from fixed-term contracts to other categories, while Figure b) shows transitions from permanent contracts. Similarly, Figure c) displays transitions from self-employment, and Figure d) presents transitions from non-employment.

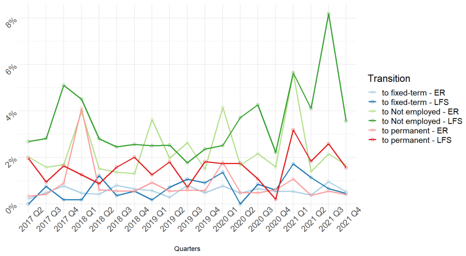
These figures confirm the findings of Tables 1 and 2 that there are only minor



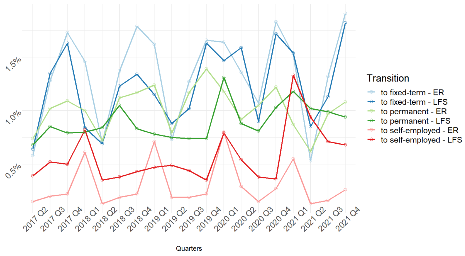
(a) Fixed-term contracts



(b) Permanent contracts



(c) Self-employer



(d) Not employed

Figure 1: Transition flows from type of contracts by quarter, year 2017-2021

Table 2: Observed transitions in AD. Years 2017-2021

Employment category $t-1$	Employment category t			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.966	0.009	0.003	0.022
Temporary contract	0.078	0.717	0.017	0.187
Self-employed	0.011	0.012	0.956	0.022
Not employed	0.030	0.061	0.012	0.897

differences in flow patterns between the LFS and AD. However, notable variations emerge when comparing different quarters. The largest transition rates occur from fixed-term contracts to non-employment and permanent contracts. As far as time differences are concerned, there is an increasing trend in flows from temporary contracts to permanent contracts, coupled with a declining trend in the transition from temporary contracts to non-employment. This consistent pattern is evident in both LFS and AD data, suggesting that there is time dependence in transition probabilities.

Table 3: Cross-classification of employment status, AD and LFS, frequencies and percentages, years 2017-2021.

Employment category, AD	Employment category, LFS				
	PE	**TE**	**SE**	**NE**	**Total**
Permanent	41326	1993	1203	1290	45812
	41.1	*2.0*	*1.2*	*1.3*	*45.6*
Temporary	1217	5442	298	1268	8225
	1.2	*5.4*	*0.3*	*1.3*	*8.2*
Self-employed	748	349	11033	1095	13225
	0.7	*0.3*	*11.0*	*1.1*	*13.2*
Not employed	1942	1394	1876	28066	33278
	1.9	*1.4*	*1.9*	*27.9*	*33.1*
Total	45233	9178	14410	31719	100540
	45.0	9.1	14.3	31.5	100.0

Note: every cell reports the relevant absolute frequency and the joint probability in italics

Table 3 presents the cross-classification of employment status from LFS and AD data. The diagonal cells concern cases where the two data sources agree on the classification. In contrast, off-diagonal values represent discrepancies in classification and indicate potential classification errors in at least one of the data sources. As table 3 illustrates, the two data sources do not align for approximately 14.6% of the total number of cases. Beyond random classification errors, these discrepancies arise from distinct reasons, as suggested by Varriale and Alfó (2023) in their analysis of employment status. Errors in AD are typically attributable to mis-specifications of statistical concepts. For example, AD lack information on irregular work, or it may encounter difficulties in correctly identifying the reference period of the information. On the other hand, errors in the LFS survey may arise from misclassification due to respondents providing incorrect answers or having an erroneous understanding of employment categories.

Table 4: Distribution of employment categories from LFS conditional on AD measurement, years 2017-2021.

Employment category, AD	**Employment category, LFS**				
	PE	**TE**	**SE**	**NE**	**Total**
Permanent contract	90.2	4.4	2.6	2.8	100
Temporary contract	14.8	66.2	3.6	15.4	100
Self-employed	5.7	2.6	83.4	8.3	100
Not employed	5.8	4.2	5.6	84.3	100
Total	45.0	9.1	14.3	31.5	100

Table 4 presents the same cross classification as table 3 but reports the percentage distribution of employment status as measured by the LFS, conditional on the AD measurement. The percentages of observations where the classification of AD employment status agrees with the classification of LFS are shown on the diagonal. Off diagonal cells represent the percentages of observations where the AD employment status is classified differently in the LFS employment status. 90.2% of cases that are recorded as permanent contracts in AD are also classified as permanent contracts according to the LFS. The relevant percentages of classification agreement for the self-employed and not employed are also quite high (83.4% and 84.3%, respectively). Accordingly, the off-diagonal values for permanent contracts, the self-employed and those not employed in the AD are rather low (below 6%). The only exception concerns the cases that are recorded as self-employed in AD as 8.3% of them are classified as not employed in the LFS. The classification mismatches are observed for temporary contracts. In fact, only 66.2% of those recorded as having a temporary contract in AD are observed as having a temporary contract in the LFS, while about 14.8% are classified as having a permanent contract and 15.4% as not employed. Figure 2 provides a temporal perspective on the distribution of table 4, highlighting the stability of this phenomenon over time.

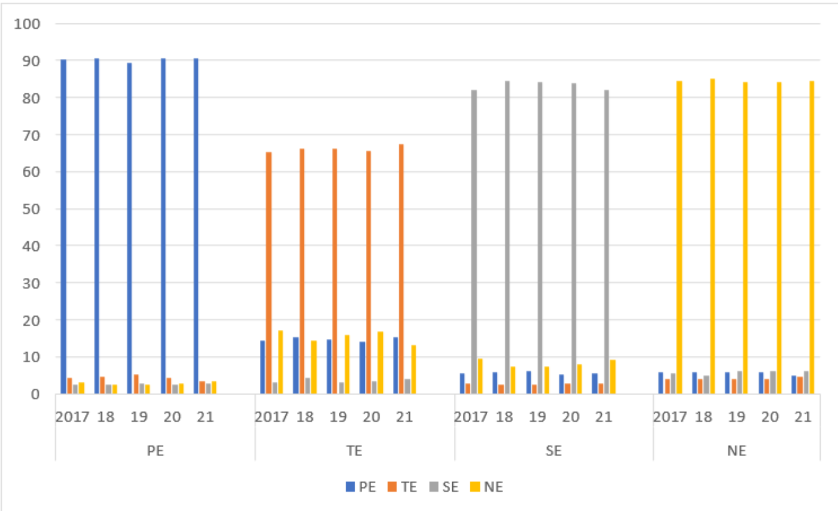


Figure 2: Distribution of employment categories by AD, LFS and year, percentages, years 2017-2021

3. THE HIDDEN MARKOV MODEL

Hidden Markov models (HMms) represent an extension of Latent Class Analysis for longitudinal data. Recently, these models have been applied in the field of employment research to correct for measurement error in mobility between employment states (Bassi et al., 2000) and to estimate employment status in the Italian employment register (Filipponi et al., 2021). Lately, Pavlopoulos et al. (2023) used a mixed HMm to evaluate the effect of measurement error on employment trajectories using linked data from the LFS and the Employment Register of the Netherlands.

Let us denote X_{it} as the "true" (latent) target variable of the model is the employment category at time t for subject i, where $t = 0, \ldots, T$ and $i = 1, \ldots, N$.

X_{it} has 4 categories, x_t: permanent contract (PE), temporary contract (TE), self-employed (SE) and not employed (NE). We use quarterly data from 2017-2021 and therefore, t runs from 0 to $T = 19$.

The variables C_{it} and E_{it} represent the two measurements for the target variable: C_{it} denotes the observed contract type of person i at time point t according to the AD and E_{it} according to LFS. Also, C_{it} and E_{it} can take the same four values of the target variable. We denote these categories by c_t and e_t. The latent contract type X_{it} follows a first-order Markov process: the true contract at time point t, X_{it}, is only directly related to the previous time point at $t-1$, $X_{i(t-1)}$.

The probability of following a certain observed path of C_{it} and E_{it} over the entire period can be expressed as follows:

$$
\begin{aligned}
P(\mathbf{C}_i = \mathbf{c}_i, \mathbf{E}_i = \mathbf{e}_i) \quad = \quad & \sum_{x_0=1}^{4} \sum_{x_1=1}^{4} \dots \sum_{x_T=1}^{4} P(X_{i0} = x_0) \prod_{t=1}^{T} P(X_{it} = x_t | X_{i(t-1)} = x_{t-1}) \\
& \prod_{t=0}^{T} P(C_{it} = c_t | X_{it} = x_t) \prod_{t=0}^{T} P(E_{it} = e_t | X_{it} = x_t)^{\delta_{it}}. \qquad (1)
\end{aligned}
$$

$P(X_{i0} = x_0)$ represent the initial state probabilities, $P(X_{it} = x_t | X_{i(t-1)} = x_{t-1})$ are the transition probabilities from $t-1$ to t, $P(C_{it} = c_t | X_{it} = x_t)$ are the measurement error probabilities for the AD, and $P(E_{it} = e_t | X_{it} = x_t)$ are the measurement error probabilities for the LFS. As we deal with categorical indicators, we will use the terms measurement and classification errors interchangeably. The indicator variable δ_{it} takes value 1 if the LFS information is available at time t and 0 otherwise. In the model, we assume the independence of the classification errors (ICE): conditional on the value of the latent variable, the observed states are independent of one another within and between time points.

As in Pavlopoulos et al. (2023), the model in equation 1 has to be extended to deal with more realistic specifications of measurement error and modelling of longitudinal change in the phenomenon of interest (i.e. employment). One of these extensions is that transition probabilities are modelled as time-varying (conditional on t and t^2), meaning that between each pair of time points we allow the model to estimate different transitions, relaxing the assumption of stationarity of the process over time. Since the ICE assumption is unrealistic, we also introduce across-time correlation in the measurement error of both indicators. The joint probability of having a particular observed state path conditionally on the across-time systematic measurement error can be expressed as follows:

$$P(\mathbf{C}_i = \mathbf{c}_i, \mathbf{E_i} = \mathbf{e}_i) = \sum_{x_0=1}^{4} \sum_{x_1=1}^{4} ... \sum_{x_T=1}^{4} P(X_{i0} = x_0) \tag{2}$$

$$\prod_{t=1}^{T} P(X_{it} = x_t | X_{i(t-1)} = x_{t-1}, t, t^2) \tag{3}$$

$$\prod_{t=0}^{T} P(C_{it} = c_t | X_{it} = x_t, X_{i(t-1)} = x_{t-1}, C_{i(t-1)} = c_{t-1}) \tag{4}$$

$$\prod_{t=0}^{T} P(E_{it} = e_t | X_{it} = x_t, X_{i(t-1)} = x_{t-1}, E_{i(t-1)} = e_{t-1})^{\delta_{it}}. \tag{5}$$

To take into account that the latent process may depend on time, we add the covariates t and t^2 in the logit modeling the transition probabilities (equation part 3). Furthermore, the error probabilities in both LFS and AD are allowed to depend on the lagged observed and lagged true contract type. Note that $X_{i(t-1)}$ and $C_{i(t-1)}$ can take on 4 values, which implies that there are 16 $(4*4)$ different sets of error probabilities in the LFS and AD indicators, one for each possible combination of lagged observed and latent contract. Because it is not meaningful to estimate freely all these error probabilities, we used a more restricted model. Specifically, we defined a constraint logit model when the same error can be made between adjacent time points and otherwise is equal to 0. This model expresses that the likelihood of making a specific error depends on whether *the same error* was made at the previous time point.

Based on a sample of independent realizations from the distribution (equation part 5), estimates of the relevant model parameters can be obtained via Maximum likelihood estimation in the Baum-Welch version (Baum et al., 1970). An extension of this algorithm is implemented in the syntax module of the Software Latent GOLD v.5.1 (Vermunt and Magidson, 2016). The final model was chosen from various alternatives. Decisions have been taken based on known modelfit measures, i.e. the Bayesian Information Criteria (BIC), the Akaike Information Criteria (AIC) and its modification, as described in Vermunt and Magidson (2016). Missing data were treated as missing at random, handled with Full Information Maximum Likelihood. This represents a proper method for recovering model parameters, reducing bias related to the missing value, and retaining all available information (Enders, 2010).

4. RESULTS

In total, we tested 9 HMms. These are presented in table 5, where we show the log-likelihood, the information criteria and the number of parameters.

In Models 1-3, we allowed for random measurement error. In more detail, in Model 1, we allowed for random measurement error in the LFS, in Model 2 in the AD, and in Model 3 in both data sources. Among the three models, Model 3 is the one presenting a better fit. Therefore, there is evidence that both sources contain at least random measurement error. In Model 4, we also allowed the LFS error to be determined by age and proxy interview. The variable on proxy interview takes the value 1 if another member of the household provided information in the survey on behalf of the reference person. The information criteria suggest that these 2 variables do not improve the model fit. Therefore, this particular error structure is not considered any further. In Models 5-9 of table 5, we used log-linear restrictions to allow for error autocorrelation. In Models 5 and 6, we estimated an extra error coefficient for the cases where the error that was made in time point $t-1$ could be repeated in t in the LFS (Model 7) or in AD (Model 8). In fact, if an error is made in quarter $t-1$ and the individual remains in the same latent state for two consecutive quarters, it is possible to repeat the same error. In Models 7 and 8, we estimated an extra error coefficient for the cases where any classification error was made in time point $t-1$. In the final model (Model 9), we combined Models 5 and 6, and we estimated an extra error coefficient for the cases where the error made in time point $t-1$ could be repeated in t both in the LFS and in AD. Model fit measures indicate that Model 9 is to be preferred over all other models.

Figure 3 provides a graphical representation of the final model of table 5, Model 9. Following the conventions, circles represent latent variables, and rectangles manifest variables; arrows connecting latent and/or manifest variables represent direct effects, which do not need to be linear.

The classification error in the two data sources is represented by the conditional probabilities $P(C_{it}=c_t|X_{it}=x_t, X_{i(t-1)}=x_{t-1}, C_{i(t-1)}=c_{t-1})$ (equation part (4)) for AD and by $P(E_{it}=e_t|X_{it}=x_t, X_{i(t-1)}=x_{t-1}, E_{i(t-1)}=e_{t-1})$ (equation part (5)) for LFS. Tables 6 and 7 show the classification error in AD and LFS according to Model 9 of table 5, where separate error (logit) parameters were estimated for the repetition of the same error between quarters $t-1$ and t. In all other cases, the probability of having an error in quarter t depends only on the

Table 5: HMm fit measures. LFS and AD data, years 2017-2021.

Model	LL	BIC(LL)	AIC(LL)	AIC3(LL)	Npar
1	-310888	622443.5	621902.1	621965.1	63
2	-352625	705918.2	705376.8	705439.8	63
3	-294941	590549.2	590007.8	590070.8	63
4	-293821	588372.6	587779.7	587848.7	69
5	-285633	572059.9	571415.5	571490.5	75
6	-279607	560008.5	559364.1	559439.1	75
7	-289556	579906.6	579262.1	579337.1	75
8	-288984	578761.7	578117.2	578192.2	75
9	-276355	553631.5	552883.9	552970.9	87

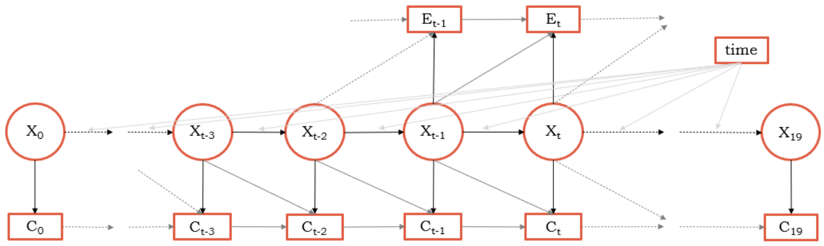


Figure 3: Path diagram for the (hidden Markov) Model 9

latent state in quarter t. In more detail, table 6 presents the probability of being observed in a certain employment category in AD conditional on the true employment category in t, the true employment category in $t-1$, and the observed value in AD in $t-1$. Table 7 presents the probability of being observed in a certain employment category in LFS conditional on the true employment category in t, the true employment category in $t-1$, and the observed value in LFS in $t-1$. Since the number of probabilities estimated is too large, we only present in tables 6 and 7, the conditional observed probabilities for cases where an error repetition is possible. These probabilities are shown in the shaded cells. For example, the probability of the shaded cell of the first row of table 6 can be interpreted as follows: if an individual in $t-1$ was employed in reality with a temporary contract but was recorded in AD as having a permanent contract, and in t (s)he is again in reality employed with a temporary contract, then (s)he has a 0.842 probability

Table 6: Selected conditional probabilities of classification error in AD, Model 9

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
TE	**PE**	**TE**	0.842	0.128	0.001	0.029
SE	**PE**	**SE**	0.949	0.000	0.050	0.001
NE	**PE**	**NE**	0.737	0.002	0.001	0.259
PE	**TE**	**PE**	0.165	0.834	0.000	0.002
SE	**TE**	**SE**	0.004	0.506	0.485	0.006
NE	**TE**	**NE**	0.006	0.289	0.003	0.702
PE	**SE**	**PE**	0.078	0.000	0.921	0.001
TE	**SE**	**TE**	0.030	0.429	0.446	0.095
NE	**SE**	**NE**	0.001	0.001	0.877	0.121
PE	**NE**	**PE**	0.523	0.001	0.001	0.475
TE	**NE**	**TE**	0.035	0.507	0.005	0.453
SE	**NE**	**SE**	0.002	0.001	0.246	0.751

(see table 6) of been again mistakenly recorded as having a permanent contract in AD. The full results of these tables are presented in the Appendix (Section 7).

For both sources, measurement errors are, in most cases, highly autocorrelated. This means that if an error is made in quarter $t-1$ and the individual remains in the same latent state in the following quarter, it is, in most cases, highly probable to repeat the same error in quarter t. For example, if a "truly" self-employed in quarter $t-1$ ($X_{i(t-1)} = SE$) was mistakenly registered in AD as having a permanent contract, and he/she is still "truly" self-employed in quarter t, then he/she has a 0.949 probability (see table 6) of being wrongly registered again as having a permanent contract in quarter t. The same error structure is observed for almost all combinations of latent/observed contract at $t-1$ and t. An important exception is for individuals who are “really” not employed in quarter $t-1$ while are observed as having a temporary contract: the probability of having the same classification error in quarter t is much lower, as it equals 0.289 (see table 6). In this situation, the probability of being correctly classified as not employed in t is 0.702 (see table 6).

In LFS, we observe a different behaviour of classification errors than in AD (tables 6 and 7). For classification errors with a “persisting” probability greater

Table 7: **Selected conditional probabilities of classification error in LFS, Model 9**

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
TE	**PE**	**TE**	0.673	0.250	0.008	0.07
SE	**PE**	**SE**	0.733	0.003	0.255	0.009
NE	**PE**	**NE**	0.778	0.005	0.007	0.21
PE	**TE**	**PE**	0.237	0.759	0.002	0.002
SE	**TE**	**SE**	0.004	0.823	0.168	0.006
NE	**TE**	**NE**	0.010	0.651	0.011	0.328
PE	**SE**	**PE**	0.287	0.002	0.708	0.003
TE	**SE**	**TE**	0.029	0.229	0.678	0.064
NE	**SE**	**NE**	0.006	0.004	0.806	0.184
PE	**NE**	**PE**	0.490	0.004	0.003	0.503
TE	**NE**	**TE**	0.049	0.389	0.012	0.550
SE	**NE**	**SE**	0.006	0.003	0.232	0.759

than 0.8 in AD, the probability of repeating the same classification error in LFS is slightly lower, such as:

$$\begin{aligned}
&P(C_{it} = PE \quad | \quad X_{it} = TE, C_{i(t-1)} = PE, X_{i(t-1)} = TE) \\
&P(C_{it} = PE \quad | \quad X_{it} = SE, C_{i(t-1)} = PE, X_{i(t-1)} = SE) \\
&P(C_{it} = PE \quad | \quad X_{it} = NE, C_{i(t-1)} = PE, X_{i(t-1)} = NE) \\
&P(C_{it} = TE \quad | \quad X_{it} = PE, C_{i(t-1)} = TE, X_{i(t-1)} = PE).
\end{aligned}$$

On the contrary, for classification errors with a "persisting" probability lower than 0.5 in AD, the LFS probability is higher. This is the case, for example, for:

$$\begin{aligned}
&P(C_{it} = TE \quad | \quad X_{it} = NE, C_{i(t-1)} = TE, X_{i(t-1)} = NE) \\
&P(C_{it} = NE \quad | \quad X_{it} = PE, C_{i(t-1)} = NE, X_{i(t-1)} = PE) \\
&P(C_{it} = NE \quad | \quad X_{it} = TE, C_{i(t-1)} = NE, X_{i(t-1)} = TE).
\end{aligned}$$

Tables 8 and 9 show the probability of being observed in an employment category in AD and LFS, given the "true" employment status. The correct classification probabilities are on the diagonals, while the off-diagonal cells represent

Table 8: Classification error in AD, Model 9

Latent employment category t	Observed employment category t			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.667	0.067	0.115	0.152
Temporary contract	0.360	0.398	0.056	0.187
Self-employed	0.403	0.041	0.321	0.235
Not employed	0.309	0.027	0.109	0.555

Table 9: Classification error in LFS data, Model 9

Latent employment category t	Observed employment category t			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.934	0.017	0.020	0.029
Temporary contract	0.118	0.651	0.032	0.199
Self-employed	0.063	0.021	0.856	0.060
Not employed	0.071	0.027	0.043	0.859

the estimated classification error probabilities. For all categories, the probabilities of correct classification are higher in LFS, and all the classification errors are larger for the AD indicator. The worst-performing category in LFS is temporary employment: as table 9 shows, individuals who, in reality, are working with a temporary contract ($X_{it} = TE$) have a probability of 0.651 of being observed as being employed with a temporary contract and a probability of 0.199 of being registered as not employed. In AD, these probabilities are 0.398 and 0.187, respectively. In AD (table 8), we also observe a high classification error for the self-employed. In fact, individuals who are really self-employed have a probability of 0.403 of being observed as working with a permanent contract, which is even higher than the probability of being observed as self-employed (0.321). In LFS (table 9), the lowest error probabilities are observed for individuals who, in reality, are employed with a permanent contract ($X_{it} = PE$) and those who are not employed ($X_{it} = NE$).

Table 10 shows the distributions of latent ("true") employment state as well as the observed distributions form the LFS and the AD. The estimates are quite

Table 10: Employment categories in LFS, AD and predicted according to Model 9. Years 2017-2021

Employment category	LFS	AD	Latent
Permanent contract	44.99	45.24	43.80
Temporary contract	9.13	8.48	11.39
Self-employed	14.33	13.28	13.56
Not employed	31.55	33.00	31.25
Number of cases	100540	711184	711184

accurate as their standard error is equal to 0.038. The average posterior probability of being employed with a temporary contract is higher than the relevant observed probabilities from the LFS and AD. This finding holds over time, as shown in table 11. These tables show the importance of accounting and controlling for measurement error when analysing labour statistics.

Transition probabilities between different employment states according to Model 9 are presented in table 12. As found in Pavlopoulos and Vermunt (2015), these latent transition probabilities are quite different from the relevant observed probabilities in both the LFS and the AD (see tables 1 and 2). Notably, all values on the main diagonal are higher for the latent transitions than for the observed transition probabilities in LFS and AD. Most importantly, latent transition probabilities from temporary employment to all other states are much lower than the relevant observed transition probabilities in both LFS and AD. For example, the 3-month latent transition probability from temporary to permanent employment is 3.7% (see table 12), while the relevant observed transition probability is 7.4% in the LFS (see table 1) and 7.8% in the AD (see table 2) . Actually, this finding illustrates that approximately half of the observed mobility from temporary to permanent employment is not real. Findings for transitions from non-employment to temporary employment are even more interesting. The 3-month latent transition probability from non-employment to temporary employment is just 2.1%, while the observed probability is 6.4% in the LFS and 6.1% in AD. This means that approximately two-thirds of the observed mobility from non-employment to temporary employment is not real.

Table 11: Proportion of temporary contract for the period between January 2017 and December 2021, predicted according to Model 9

t	**LFS**	**AD**	**Latent**
0	7.56	6.49	6.77
1	8.95	8.33	9.30
2	9.15	8.57	10.56
3	8.87	8.55	11.16
4	9.17	8.27	11.6
5	9.58	9.46	12.01
6	10.18	9.40	12.19
7	9.22	9.01	12.09
8	8.96	7.89	11.95
9	9.74	8.94	11.92
10	10.19	8.71	11.85
11	9.99	8.68	11.60
12	8.96	7.77	11.30
13	8.20	7.06	11.09
14	8.57	8.00	11.25
15	8.58	8.12	11.45
16	8.22	7.73	11.46
17	8.87	9.12	11.91
18	9.39	9.51	12.80
19	10.13	10.03	13.89

Table 12: Latent transitions according to Model 9. Years 2017-2021

Latent employment category $t-1$	**Latent employment category t**			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.988	0.005	0.001	0.006
Temporary contract	0.037	0.939	0.002	0.022
Self-employed	0.001	0.005	0.991	0.003
Not employed	0.005	0.024	0.004	0.967

5. DISCUSSION AND CONCLUSIONS

This paper illustrated the value of using an HMm with multiple indicators in accounting for measurement error on the role of flexible employment in the life course. For our research, we used Italian individual-level data from different sources, namely the Labour Force Survey and Administrative sources, for the period 2017-2021. The HMm takes into account the longitudinal structure of the data and allows us to evaluate different measurement error structures in the two data sources. In particular, we studied whether measurement errors in the two data sources can be correlated in time.

As suggested by the literature, our results show that both LFS and AD suffer from measurement error and cannot be used as a "golden standard". Furthermore, the probability of the same error recurring is different in the LFS and the AD. An in-depth analysis of these characteristics may help improve the sources' quality.

The model results can also be used to estimate the error-corrected distribution of employment states as well as the error-corrected transition rates between these states. Notably, in this paper, we found that temporary employment in Italy is much more common according to our HMm than observed in the LFS and AD. Probably the most striking finding of this study is that mobility from temporary to permanent employment is (according to HMm) half of what we observe in LFS or AD. Moreover, mobility from non-employment to employment concerns only transitions to temporary employment. But even then, this mobility is one-third of what we observe in LFS or AD. These results are of utmost importance for policymakers. They show that the Italian labour market is much less mobile than the data suggests.

To provide richer results, the structural part of the model can be extended by introducing covariates and by accounting for unobserved heterogeneity. The measurement part of the model can be enriched by testing more specifications of systematic error. In addition, sensitivity analyses to the model's assumptions can be carried out using Monte Carlo-type simulations.

The paper sheds new light on the role that errors in sources could play in the assessment of labour mobility, the real size of permanent jobs and the specificities of self-employment. Of course, a precise analysis of the causes of measurement errors in sources will be important in order to reduce their occurrence wherever possible. For example, some statistical units are not covered by administrative information, e.g. jobs with a salary below a certain threshold. It will be interesting to analyse whether this information can be obtained from other sources. Furthermore, some discrepancies between the LFS and the AD are due to temporal shifts in the recording of contracts. In the future, it might be useful to try to identify these contracts in order to harmonize their time reference and then evaluate their impact on the results of the HMM.

In the future it will also be important to analyse in detail the situations in which the LFS and the AD report different information. This analysis will make it possible to obtain useful information to try to correct situations where there are systematic differences between LFS and AD coding, e.g. due to definitional problems, which we are not aware of.

6. NOTES

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Any opinions and conclusions expressed are those of the authors and do not necessarily respect the views of the Italian national institute of statistics.

7. APPENDIX

Table 13: Selected conditional probabilities of classification error in AD, Model 9 (a)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**PE**	**PE**	0.988	0.002	0.001	0.009
TE	**PE**	**PE**	0.988	0.002	0.001	0.009
SE	**PE**	**PE**	0.988	0.002	0.001	0.009
NE	**PE**	**PE**	0.988	0.002	0.001	0.009
PE	**PE**	**TE**	0.054	0.768	0.007	0.171
TE	**PE**	**TE**	0.842	0.128	0.001	0.029
SE	**PE**	**TE**	0.054	0.768	0.007	0.171
NE	**PE**	**TE**	0.054	0.768	0.007	0.171
PE	**PE**	**SE**	0.007	0.004	0.978	0.011
TE	**PE**	**SE**	0.007	0.004	0.978	0.011
SE	**PE**	**SE**	0.949	0.000	0.050	0.001
NE	**PE**	**SE**	0.007	0.004	0.978	0.011
PE	**PE**	**NE**	0.008	0.009	0.004	0.979
TE	**PE**	**NE**	0.008	0.009	0.004	0.979
SE	**PE**	**NE**	0.008	0.009	0.004	0.979
NE	**PE**	**NE**	0.737	0.002	0.001	0.259
PE	**TE**	**PE**	0.165	0.834	0.000	0.002
TE	**TE**	**PE**	0.988	0.002	0.001	0.009
SE	**TE**	**PE**	0.988	0.002	0.001	0.009
NE	**TE**	**PE**	0.988	0.002	0.001	0.009
PE	**TE**	**TE**	0.054	0.768	0.007	0.171
TE	**TE**	**TE**	0.054	0.768	0.007	0.171
SE	**TE**	**TE**	0.054	0.768	0.007	0.171
NE	**TE**	**TE**	0.054	0.768	0.007	0.171
PE	**TE**	**SE**	0.007	0.004	0.978	0.011
TE	**TE**	**SE**	0.007	0.004	0.978	0.011
SE	**TE**	**SE**	0.004	0.506	0.485	0.006
NE	**TE**	**SE**	0.007	0.004	0.978	0.011
PE	**TE**	**NE**	0.008	0.009	0.004	0.979
TE	**TE**	**NE**	0.008	0.009	0.004	0.979
SE	**TE**	**NE**	0.008	0.009	0.004	0.979
NE	**TE**	**NE**	0.006	0.289	0.003	0.702

Table 14: Selected conditional probabilities of classification error in AD, Model 9 (b)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**SE**	**PE**	0.078	0.000	0.921	0.001
TE	**SE**	**PE**	0.988	0.002	0.001	0.009
SE	**SE**	**PE**	0.988	0.002	0.001	0.009
NE	**SE**	**PE**	0.988	0.002	0.001	0.009
PE	**SE**	**TE**	0.054	0.768	0.007	0.171
TE	**SE**	**TE**	0.03	0.429	0.446	0.095
SE	**SE**	**TE**	0.054	0.768	0.007	0.171
NE	**SE**	**TE**	0.054	0.768	0.007	0.171
PE	**SE**	**SE**	0.007	0.004	0.978	0.011
TE	**SE**	**SE**	0.007	0.004	0.978	0.011
SE	**SE**	**SE**	0.007	0.004	0.978	0.011
NE	**SE**	**SE**	0.007	0.004	0.978	0.011
PE	**SE**	**NE**	0.008	0.009	0.004	0.979
TE	**SE**	**NE**	0.008	0.009	0.004	0.979
SE	**SE**	**NE**	0.008	0.009	0.004	0.979
NE	**SE**	**NE**	0.001	0.001	0.877	0.121
PE	**NE**	**PE**	0.523	0.001	0.001	0.475
TE	**NE**	**PE**	0.988	0.002	0.001	0.009
SE	**NE**	**PE**	0.988	0.002	0.001	0.009
NE	**NE**	**PE**	0.988	0.002	0.001	0.009
PE	**NE**	**TE**	0.054	0.768	0.007	0.171
TE	**NE**	**TE**	0.035	0.507	0.005	0.453
SE	**NE**	**TE**	0.054	0.768	0.007	0.171
NE	**NE**	**TE**	0.054	0.768	0.007	0.171
PE	**NE**	**SE**	0.007	0.004	0.978	0.011
TE	**NE**	**SE**	0.007	0.004	0.978	0.011
SE	**NE**	**SE**	0.002	0.001	0.246	0.751
NE	**NE**	**SE**	0.007	0.004	0.978	0.011
PE	**NE**	**NE**	0.008	0.009	0.004	0.979
TE	**NE**	**NE**	0.008	0.009	0.004	0.979
SE	**NE**	**NE**	0.008	0.009	0.004	0.979
NE	**NE**	**NE**	0.008	0.009	0.004	0.979

Table 15: Selected conditional probabilities of classification error in LFS, Model 9 (a)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**PE**	**PE**	0.977	0.008	0.007	0.009
TE	**PE**	**PE**	0.977	0.008	0.007	0.009
SE	**PE**	**PE**	0.977	0.008	0.007	0.009
NE	**PE**	**PE**	0.977	0.008	0.007	0.009
PE	**PE**	**TE**	0.088	0.696	0.021	0.195
TE	**PE**	**TE**	0.673	0.25	0.008	0.07
SE	**PE**	**TE**	0.088	0.696	0.021	0.195
NE	**PE**	**TE**	0.088	0.696	0.021	0.195
PE	**PE**	**SE**	0.022	0.012	0.934	0.031
TE	**PE**	**SE**	0.022	0.012	0.934	0.031
SE	**PE**	**SE**	0.733	0.003	0.255	0.009
NE	**PE**	**SE**	0.022	0.012	0.934	0.031
PE	**PE**	**NE**	0.028	0.021	0.031	0.921
TE	**PE**	**NE**	0.028	0.021	0.031	0.921
SE	**PE**	**NE**	0.028	0.021	0.031	0.921
NE	**PE**	**NE**	0.778	0.005	0.007	0.21
PE	**TE**	**PE**	0.237	0.759	0.002	0.002
TE	**TE**	**PE**	0.977	0.008	0.007	0.009
SE	**TE**	**PE**	0.977	0.008	0.007	0.009
NE	**TE**	**PE**	0.977	0.008	0.007	0.009
PE	**TE**	**TE**	0.088	0.696	0.021	0.195
TE	**TE**	**TE**	0.088	0.696	0.021	0.195
SE	**TE**	**TE**	0.088	0.696	0.021	0.195
NE	**TE**	**TE**	0.088	0.696	0.021	0.195
PE	**TE**	**SE**	0.022	0.012	0.934	0.031
TE	**TE**	**SE**	0.022	0.012	0.934	0.031
SE	**TE**	**SE**	0.004	0.823	0.168	0.006
NE	**TE**	**SE**	0.022	0.012	0.934	0.031
PE	**TE**	**NE**	0.028	0.021	0.031	0.921
TE	**TE**	**NE**	0.028	0.021	0.031	0.921
SE	**TE**	**NE**	0.028	0.021	0.031	0.921
NE	**TE**	**NE**	0.010	0.651	0.011	0.328

Table 16: Selected conditional probabilities of classification error in LFS, Model 9 (b)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**SE**	**PE**	0.287	0.002	0.708	0.003
TE	**SE**	**PE**	0.977	0.008	0.007	0.009
SE	**SE**	**PE**	0.977	0.008	0.007	0.009
NE	**SE**	**PE**	0.977	0.008	0.007	0.009
PE	**SE**	**TE**	0.088	0.696	0.021	0.195
TE	**SE**	**TE**	0.029	0.229	0.678	0.064
SE	**SE**	**TE**	0.088	0.696	0.021	0.195
NE	**SE**	**TE**	0.088	0.696	0.021	0.195
PE	**SE**	**SE**	0.022	0.012	0.934	0.031
TE	**SE**	**SE**	0.022	0.012	0.934	0.031
SE	**SE**	**SE**	0.022	0.012	0.934	0.031
NE	**SE**	**SE**	0.022	0.012	0.934	0.031
PE	**SE**	**NE**	0.028	0.021	0.031	0.921
TE	**SE**	**NE**	0.028	0.021	0.031	0.921
SE	**SE**	**NE**	0.028	0.021	0.031	0.921
NE	**SE**	**NE**	0.006	0.004	0.806	0.184
PE	**NE**	**PE**	0.490	0.004	0.003	0.503
TE	**NE**	**PE**	0.977	0.008	0.007	0.009
SE	**NE**	**PE**	0.977	0.008	0.007	0.009
NE	**NE**	**PE**	0.977	0.008	0.007	0.009
PE	**NE**	**TE**	0.088	0.696	0.021	0.195
TE	**NE**	**TE**	0.049	0.389	0.012	0.55
SE	**NE**	**TE**	0.088	0.696	0.021	0.195
NE	**NE**	**TE**	0.088	0.696	0.021	0.195
PE	**NE**	**SE**	0.022	0.012	0.934	0.031
TE	**NE**	**SE**	0.022	0.012	0.934	0.031
SE	**NE**	**SE**	0.006	0.003	0.232	0.759
NE	**NE**	**SE**	0.022	0.012	0.934	0.031
PE	**NE**	**NE**	0.028	0.021	0.031	0.921
TE	**NE**	**NE**	0.028	0.021	0.031	0.921
SE	**NE**	**NE**	0.028	0.021	0.031	0.921
NE	**NE**	**NE**	0.028	0.021	0.031	0.921

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