Active Labor Market Policies and Transitions to Permanent Employment. The Potential of Administrative Data

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Active labor market policies (ALMPs) are meant to help the unemployed and the economically disadvantaged to find a job. They usually include a combination of job search assistance, training and wage subsidies. In the last decades, few public policies have received such in-depth scrutiny by economists and statisticians and have been evaluated with so many different empirical strategies (Heckman at al. 1999). Nevertheless, one of the main insights from this rich literature is that there is substantial heterogeneity in the impact of ALMPs. Thus, policy makers are often left without clear guidance on which social groups benefit the most from these interventions and which types of programs are worthwhile social investments.

This guidance is particularly important in Italy for at least two reasons. Firstly, it is one of the advanced countries where investments in ALMPs are the lowest (Mandrone, 2014). Secondly, recent reforms have tried to introduce a model of flexicurity combining labor market flexibility (i.e. lower firing costs) with increased security for workers and not for jobs (i.e. broader ALMPs). However, while the first pillar of the model has been implemented, the second one is still work in progress.

This chapter aims at shedding some light on the effectiveness of existing ALMPs. The maib goal of this contribution is to show how it is possible to combine three sources of administrative data, namely, the system of Compulsory Communications (Comunicazioni Obbligatorie, CO) managed by the Ministry of Labor and Social Policy; the archives of local agencies in charge of active labor market policies (PES) and the equivalent economic/financial status indicator (EESI) data drawn from fiscal assistance centers. Administrative microdata, which only recently have been released in Italy for research purposes, have the advantage of providing information almost in real time and to be accurate at local domains. For our purposes, they allow to trace job transitions to a permanent position, investigate how workers move across jobs, identify unemployment spells, program participation and different types of labor contracts. We also discuss possible identification strategies to assess the effectiveness of active labor market programs which exploit discontinuity stemming from labor market reforms. Finally, we use event history analysis to model the time to exit to a permanent job as a function of individual characteristics, previous labor experience and participation to programs.

Admittedly, our data have a number of limitations. In the first place, they refer to the period 2011-2014, which follows the crisis and includes the Fornero reform (2012) but leaves out the Jobs Act approved in 2015. Secondly, they only relate to the Tuscan province of Pistoia. Hence, this work is still preliminary and in the final section we highlight some possible directions for future research.

1 Introduction

Since the 2008 financial crisis, unemployment rates have been persistently high in most EU countries. Mainly due to its structural weaknesses, Italy is one of the European States which have been most damaged by the crisis. The Italian labor market is highly heterogeneous across gender and age factors with the marginalization of specific subgroups of population, in particular women and young people. There are also clear disparities across local labor markets within the country. Moreover, after the introduction of new temporary contracts at the end of the nineties, there is a strong dualism between permanent and temporary workers.

A number of labor market measures have been introduced in 2012 (For-nero labor reform), which attempted to reduce both employment protection for permanent workers and the overuse of the less protected temporary contracts.

Active labor market policies (ALMPs) are one of the main instruments to mitigate the effect of the crisis. With the recent Jobs Act (2015), Public Employment Services (PES), which were previously decentralized to local governments, are moving back to centralization. A national employment agency is now responsible for ALMPs, including its coordination with social benefit providers. To some extent, this new centralization seems at odds with a growing demand for place-based policies with a high level of selectivity (to account for scarcity of resources).

The main goal of this chapter is to show the potential of administrative microdata in monitoring the short term evolution of the labor market, at a very detailed level, and to evaluate the effectiveness of labor policies. With respect to survey data, administrative data, which have only recently been released for research, have the advantage of being continuously registered and of being accurate at local domains. Unfortunately, these data are not released in workable formats and, to fully exploit their potential and to provide useful support to policy makers, a number of data editing and processing procedures need to be established (see, for example, Baldi et al. 2011).

We focus on the 2011-2014 period, which follows the crisis and includes the Fornero reform (2012) but leaves out the recent Jobs Act reform (2015)[1]. Due to data limitations, our analysis is confined to the Tuscan province of Pistoia.

We exploit three different sources of administrative data: the system of Compulsory Communications (Comunicazioni Obbligatorie, CO) managed by the Ministry of Labor and Social Policies; the archives of local agencies in charge of active labor market policies (PES); and the equivalent economic/financial status indicator (EESI) provided by fiscal assistance centers. To the best of our knowledge, this is the first attempt in using EESI data in conjunction with CO and ALMP datasets.

Our analysis encompasses various steps. As a preliminary descriptive analysis, we trace job transitions to a permanent position and investigate how workers move across jobs, experiencing unemployment, program participation, or different types of labor contracts. We analyze the relationship between types of contracts and individual characteristics (age, gender, residential place, etc.) to verify whether there are types of contracts, which are an obstacle to gaining a better and more stable job, looking at specific segments of population.

An important issue in the ALMPs evaluation literature is the difficulty in controlling for selection bias, which may lead to either upward or downward distorsion of results (Bruno et al. 2013; Caliendo and Schmidl, 2015; Card et al. 2010, 2015; Martin, 2014). Most convincing identification strategies tried to exploit differences in the applicability of ALMPs (for

[1]For a preliminary assessment of the impact of the 2015 policies, see Sestito and Viviano (2016).

example, the eligible age for specific programs), or time-discontinuity due to the entry into force of a given reform. In this chapter, we use event history analysis to model the time to exit to a permanent job as a function of demographic characteristics, previous labor experience and participation to ALMPs programs. Assuming selection on observables, the program average effect can be measured by the difference between the exit rate to a steady job of those who entered a specific program and the exit rate of those who did not. Moreover, we also provide some preliminary evidence stemming from the time-discontinuity due to the Fornero labor reform.

The chapter is organized as follows: section 2 briefly presents the administrative data sources; section 3 provides a descriptive analysis of our dataset with a focus on specific policy measures introduced by the Italian government in 2012 (Fornero labor Reform). Section 4 presents some results from a survival model for the time to exit to a permanent job. Our conclusions are expounded in section 5.

2 Data sources

The database of Compulsory Communications (Comunicazioni Obbligatorie, CO), managed by the Ministry of Labor and Social Policies, includes information from all the subjects responsible for communicating the start, the termination or the transformation of a job position. Since 1 March 2008, every employer, in the private and in (part of) the public sector, must use the CO electronic service to notify any variation in the status of the employees.

Potentially, the CO data set contains a rich set of variables concerning the employer, the worker and the job position, so that statistical analyses based on this administrative source might greatly enhance the informative support to policy making (Baldi et al., 2011). Until recently, most Italian studies of labor market dynamics were either based on the Italian Labor Force Survey provided by Istat or on the Work Histories Italian Panel (WHIP) provided by Laboratorio Riccardo Rivelli. CO data convey important and so far under-investigated information on employment dynamics in Italy (see Chelli and Gigliarano, 2012; Anastasia et al., 2016). Furthermore, CO have both the advantage of being continuously registered and of guaranteeing the availability of longitudinal microdata.

However, because of the decentralization of the data-collection process to the regions, the quality of micro data differs quite a lot across different regions. Our data refer to one province (Pistoia) of the region of Tuscany and cover the period from January 2011 to December 2014. It is important to bear in mind that people who were never employed (the unemployed or people not in the labor force) or the employed in open-ended contracts whose status never changed since January 2011, have not been observed.

For the same period, we have acquired micro data from Public Employment Services (PES), reporting individual characteristics (such as age, gender, citizenship) and ALMPs actions (date and type of action). The quality of the data is heterogeneous, depending on the pertaining territorial office and also on the staff member who registered the information. For these reasons, accurate quality checking and data revision were a preliminary requirement.

We also have individual data available from ESSI (Equivalent Economic Situation Indicator) statements coming from CGIL fiscal assistance centers (the Italian most important workers union) in the province of Pistoia. Our purpose is to understand whether EESI data are useful in improving analysis of labor market dynamics at the local level, and to what extent EESI information fits the evidence stemming from other data sources.

The Equivalent Economic Situation Indicator was introduced in Italy in 1998 to measure the economic condition of citizens requesting for mean-test welfare programs which take into account household composition. Citizens who want to access mean-tested welfare programs are required to submit a formal statement containing all the necessary data to compute the EESI. The field of application is extremely wide and heterogeneous and mainly concerns the provision of services (benefits) for which a principle of rationing related to the applicants' economic conditions, applies. Such data are collected in a database (the EESI database).

Besides its administrative objectives, the EESI database may be used to analyse the economic conditions of the population at the sub-regional level, even if EESI data are typically affected by a self-selection bias, in that only persons eligible for mean-test welfare programs become part of the database. With respect to tax registers data, the EESI database contains information pertaining to the economic conditions of both individuals and households. With respect to a sample survey, the EESI database provides information on household income and wealth at local level. Further, the EESI data allows one to focus on populations scarcely covered by sample surveys (single with children or family with more than two children). However, the EESI database suffers from the typical flaws of administrative data (as it is fragmentary and not properly collected). It is reasonable to expect an improvement in the quality of data starting from the recent EESI reform (2015; for a preliminary monitoring report see Ministero del lavoro e delle politiche sociali, 2016).

3 Descriptive analysis

We present some descriptive statistics based on CO and PES data for the province of Pistoia in the period 2011-2014. Over this period, our data include 258,628 communications, involving 92,655 workers (53.5% women and 46.5% men) and 129,117 ALMPs, administered to 61,332 individuals (53.1% women and 46.9% men).

Table 1 shows the number of hires and workers by year. The average turn-over per year is also reported. On average, each worker changes (or transforms) his/her employment contract almost 3 times during the period, while the average turn-over per year is about 1.7.

The distribution of ALMPs actions and of beneficiaries by year is reported in Table 2. The average number of ALMPs actions per person increased over time, going from 1.4 in 2011 to 1.6 in 2014. It is worth noting that the per capita number of ALMPs interventions throughout the whole period was 2.1, therefore higher than annual values, thus suggesting that a relevant number of individuals tends reiterate their applications for PES services. This can be explained as a sort of "customer loyalty", in that less qualified individuals with low social capital view employment services as the only way to exit from unemployment/inactivity (see Reyneri, 2005) .

We have classified the different types of contract into four main categories of interest (open-ended, fixed-term, apprenticeship, Project work/Co. Co. Co.) in addition to a residual one (others). The distribution of hires by type of contract and gender is presented in Table 3. Percentages of males and females are roughly balanced by type of contract, with some appreciable differences with respect to fixed term contracts (4.2% in favour of women) and open-ended contracts (2.8% in favor of men).

Table 4 illustrates how different contract types are distributed according to workers' age groups. The fixed term contract plays a prominent role in each age group, ranging from 45.3% for young workers to 60% for the 30-49 age group. However, this does not necessarily lead to a permanent position. Table 5 displays transition frequencies from one contract to another (Table 5) and we can see that only 10.98% of these contracts give rise to open-ended employment, while most of these workers (56.94%) are re-employed with fixed-term contracts. When employed in permanent jobs (19.7%), workers maintain the same job in 63.59% of cases (see censoring column in Table 5) throughout the observation period, while those who change jobs are mostly hired with a new open-ended contract (21.87%). Only 11.35% experiences a downgrade to fixed term contracts. Apprenticeships (4.4%), whose natural result is supposed to be the conversion to a permanent job, mostly tend to be renewed by the same or other employers (31.69% and 47.45%, respectively). We can observe transitions to open ended positions only in 7.71% of our sample.

We are also interested in studying the effects of the Fornero labor market reform. To explore whether it had any sizeable impact on job creation, Figure 3 reports the quarterly number of total hires. If anything, after the reform, the overall number of jobs which have been created, decreased. Of course, several additional factors (beyond the reform itself) may explain this pattern. As mentioned, one of the main goals of the new law was to encourage the creation of permanent positions. Figure 4 plots the share of permanent jobs created during each quarter. Contrary to reform intentions, the share of new permanent positions declined. Again, this pattern may be due to different factors but constitutes prima facie evidence of the failure of the reform. An additional objective of the Fornero reform was to establish the apprenticeship contract as the main route leading to a permanent contract. Figure 5 depicts the share of apprenticeship contracts among hires who are 29 or younger (apprenticeship is only legal under this threshold). Again, it appears that reform implementation fell short of the government's expectations. This seems to be confirmed by the pattern of overall young hires which is remarkably similar to the pattern concerning older workers (Figure 6).

To measure job quality, we associated a score (on a scale from 1 to 3) to each type of contract, according to its wage levels, social security protection and union intensity. From this ranking, we computed a composite index of the contractual quality for subgroups of females and males (ranging from 0%, minimum contractual quality, to 100%, maximum contractual quality), which resulted in 49.3% for women and 50.7% for men over the whole period of observation[2]. Looking at the time trend of the index, we can observe a progressive slow decrease in the quality of contracts for females (starting from 49.8% in 2011 and ending to 47.9 in 2014), while males present a more varied trend, even if over 50% in most cases (see Figure 1). In Figure 2 the contractual quality index is reported by age subgroups: looking at the whole period, the index is higher for the 30-49 age group, followed by the over 50 and youth. Trends for the three age groups appear similar, showing a progressive quality decrease from 2011 to 2014.

Tables 5 and 6 result from the joint analysis of COB and PES data[3].

[2]The composite index is computed as follows for a set of n units: $\frac{(\sum_{i=1}^{n} w_i/3n)-min}{max-min}*100$ with $w_i = 1, 2, 3$.

[3]For the sake of facilitating interpretation, we aggregated some similar typologies of ALMPs and proposed a classification which accounts for different level of effort required

Hires after an ALMP action amount to 65,534 (51.2% women and 48.8% men), which represents 25.3% of total hires observed in the period (equal to 258,628).

As shown in Table 6 (see ALMP column) subjects accessing PESs usually take advantage of more than an ALMP action before finding a job, so that their placement should possibly be attributed to the overall path. Looking at transition frequencies ALMP-to-ALMP (Table 7) observed ALMP interventions appear to follow the procedure recommended by European Union (Bresciani, 2006): Counseling → Training → Stage/Internship → effective job placement.

As a whole, the key role of counseling clearly emerges, both at the beginning of the search process and subsequently. After the first counseling intervention, 27.63% of job seekers access to additional counseling. Moreover, after training activities (both those directly supplied by PESs and training vouchers), job seekers often go back to counseling (72.69% and 87.89%, respectively).

In the next sections, we investigate whether and to what extent the process undertaken by job seekers requiring PESs services is related to the time needed to achieve a god quality position. Individual characteristics, labor market conditions and policy instruments are likely to explain this variable.

4 Time to exit to a permanent job

We exploit standard survival analysis tools (also known as event history analysis or duration modeling) to describe exits into a permanent job, conditional on a set of covariates (see Blossfeld et al. 2007 for a general introduction; see Caretta et al. 2013 for a recent application to Italian labor market). This class of models, even if originally developed in biostatistics, has been largely applied in a variety of social research fields: labor market studies, social inequality studies, demographic analyses, educational studies, political science research, marketing applications, and so on.

Here, a hazard based duration model is applied to the length of time spent before moving into a high quality job position. The dependent variable is the number of months (duration) that an individual spends in low quality employment (or unemployment/out of labor force) before exiting to the first steady/protected job position. We use the classification

either by the PES operators or by the individuals accessing PES (IRPET, 2014). Both Interviews ex D.lgs 18100, which are conditions to access employment services, and generally unspecified actions, have been excluded from our analysis.

introduced in Section 2 to characterize high quality job positions, which include most (but not all) open-ended contracts. Survivor analysis allows us to model the length of time spent in a given state before moving into another state, taking into account the presence of censored and left-truncated data. Censoring arises because not all the full history of the units is observed until the event of interest occurs (usually denoted as "failure" in survival analysis) while left truncation depends on individuals becoming at risk or even fail before starting observation.

Let T_j be a continuous random variable, with probability distribution f(t), representing the length of each individual j spell. The survival function for the j-th individual, or the probability that his spell T is of length at least equal to t, is given by the following:

$$S(t) = 1 - F(t) = Pr(T_J > t) = \int_t^\infty f(s)ds$$

where $F(t) = Pr(T_j \leq t) = \int_0^t f(s)ds$ is the cumulative distribution function of T. We also define the hazard rate for individual j at time t as the marginal probability of achieving a permanent job position, conditional on not having achieved it before time t:

$$h(t) = Pr(t < T_j < t + dt|T_j > t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{s(t)}$$

Within this class of models, we specify the semiparametric Cox proportional hazard model (Cox, 1972; 1975), which avoids parametric assumptions on the hazard function at baseline and assumes a baseline hazard that is common to all the individuals in the study. In the Cox model, the hazard for the j-th individual in the data is assumed to be:

$$h(t|x_j) = h_0(t)\exp(\beta' x_j)$$

where β' is the vector of regression coefficients; x a vector of covariates which influence the hazard rate; and $h_0(t)$ is the baseline hazard function. The effects of covariates can only induce proportional shifts in the transition rate but cannot change its shape. The Cox model has been widely used, although the proportionality assumption restricts the range of possible empirical applications. It can be a useful starting point when one is mainly interested in the magnitude and direction of the effects of observed covariates, controlling for time-dependence.

Table 9 reports the empirical survivor functions based on the Kaplan-Meier non-parametric estimator, showing the shares of subjects who, at specific time points after the beginning of observation, are still waiting for a steady job. Starting from 95%, after about 12 months the probability of waiting decreases to 0.77% (conversely, the probability of achieving a permanent position increases to 23%). After 36 month this probability is equal to 70%.

Table 10 presents the results from a continuous semiparametric Cox model with baseline constant covariates describing individual characteristics (age, gender, education level) and time varying covariates including, for each subject, ALMPs intervention at $t - 1$ (if any), previous training experience, type of contract at $t - 1$, total number of ALMPs actions until t, total number of job position until t as a proxy of job experience. We also included a variable representing the Fornero labor reform (with value 1 from the date of entering into force). The model is estimated on the integrated dataset resulting from merging COB and ALMPs data (amounting to 59,623 subjects and 177,978 events, with the exception of subjects with a single recorded event). Robust standard errors have been computed, adjusted for clusters of individuals.

We can easily interpret the estimated hazard ratios (reported in the table instead of coefficients of the linear predictor): a ratio greater than 1 means that the variable positively correlates with the probability to move to a high quality job position, given that the same position has not been achieved before; otherwise if the hazard ratio is lower than 1, the variable contributes to reducing this probability, therefore increasing survival (waiting for a steady job) time. Our findings show the following results: age positively correlates with the occurrence of the outcome; women have a positive significative hazard ratio, which is in line with previous literature stating that women achieve first stabilization before men. Both the number of ALMPs actions and previous job positions negatively correlate with the outcome: these results would suggest that frequent job interruptions can negatively affect subsequent working life with fewer employment opportunities (see also Caretta et al., 2013). Moreover, subjects with a high number of ALMPs actions may correspond to less qualified human capital which becomes tied to the PES for a longer time. An ALMP action in the previous spell increases the likelihood of stabilization; while specific training activities do not appear to significantly affect the obtaining of a steady position, which, in line with other literature, highlights a lock-in effect. Looking at different typologies of previous job contracts, we found a positive effect of fixed-term contracts and a negative effect of both apprenticeship and project/co.co.co. work, with respect to the set of other categories. Lastly, the 'Fornero' labor reform shows an overall significative negative effect. Less qualified workers show a positive hazard ratio, while a negative effect is observed for the high qualified.

We now focus on the reduced sample obtained looking at the subgroup of subjects also present in the EESI data set. The EESI data set contains information on 24550 subjects for the period at hand. The merging processing results in 5658 subjects (those who also appear at least one time in the CO database). It is necessary to bear in mind that this subgroup represents a self-selected subpopulation where heads of households are eligible for mean-test welfare programs.

We mostly consider our simple exercise as a way to highlight potential advantages of exploiting multiple administrative archives, possibly available at the local level. For the present, we include the standardised EESI indicator and personal income as time-varying covariates (referred to the previous year), as well as the size of the household (number of members) as a baseline covariate.

Results in Table 11 show that most variables included in the previous model loss significance, however the standardized EESI indicator appears to significantly reduce the probability of stabilization at time t, suggesting that the overall household economic situation may convey relevant information for our analysis. Conversely, we found a positive association between the probability of stabilization and the level of personal income, which may act as a measure of the quality of previous job positions with a probability to be converted in a permanent position.

These results are preliminary, but, in our opinion, worthy of further investigation. We aim to extend the analysis to draw proper causal inferences. In fact, even if event history models are a useful approach to uncover causal relationships, opportunities for causal inferences depend on the set of data at hand and on (untestable) assumptions one is available to accept (Ham and Lalonde, 1996). Causal mechanisms imply a counterfactual reasoning (Holland, 1986; for a recent book on causal inference see Imbens and Rubin, 2015). Effectiveness evaluation analyses should determine how far a specific intervention contributed in changing the pre-existing situation, i.e., whether the situation observed after the intervention is different from the one we would have observed in its absence. We intend to proceed along two paths: on the one hand, based on "selection on observable assumptions", we plan to combine matching techniques (to balance the distribution of covariates among program beneficiaries and not beneficiaries) with survival analysis techniques; on the other, we will exploit "frailty" models to account for observations conditionally different in terms of their hazards due to unobserved heterogeneity (Lancaster, 1979).

5 Concluding remarks

In this chapter, we focussed on a local context (one Italian Province) for the period 2011-2014, which follows the crisis and includes the Fornero reform. The local perspective is both a limitation and a strength of our approach, because of the focus on local government actors. We used individual micro data coming from three different sources of administrative data. The joint analysis of job transitions, ALMPs participation and EESI family statements may provide a novel contribution to an integrated view of welfare policies at the local level. Unfortunately, the quality of data collection is not always befitting and strongly depends on the local institutions in charge. The opportunity to access the actual and complete administrative data would represent a valuable decision support tool for policy makers and would allow scholars to evaluate the effectiveness of the programs independently.

Our analysis traced job transitions to a steady position and investigated how workers move across jobs, experiencing unemployment, program participation, or different types of labor contracts. We used standard event history analysis to model the time to exit to a steady job as a function of individual characteristics, previous labor experience and participation to programs. Results, although preliminary, highlights some interesting issues. In particular, we found that people experimenting frequent contractual changes or receiving advantages from a certain number of ALMPs actions are in worse position in achieving the first stable position, suggesting a dispersive path. These results are in line with previous literature stating that frequent job interruptions can negatively affect subsequent working life with fewer employment opportunities. Furthermore, we argued that subjects involved in a high number of ALMPs actions may correspond to less qualified human capital that remains caged inside PESs mechanism for too long.

We aim to extend our analysis in several directions. As a first step, we plan both to combine matching techniques (to balance the covariates distribution among program beneficiaries and not-beneficiaries) with survival analysis techniques, and exploit “frailty” models to account for observations conditionally different in terms of their hazards due to unobserved heterogeneity.

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Tables and Figures

Table 1: Number of hires and workers (2011-2014).

Year	Hires	Workers	Turn-over
2011	71517	38728	1.8
2012	67692	36792	1.8
2013	59411	34103	1.7
2014	60008	34556	1.7
Whole period	258628	92655	2.8

Table 2: Number of ALMP interventions and beneficiaries (2011-2014).

Year	ALMP	Beneficiaries	ALMP per person
2011	6569	4589	1.4
2012	14337	10251	1.4
2013	53506	34551	1.5
2014	54705	33731	1.6
Total	129117	61332	2.1

Table 3: Hires by contractual type and gender, percentages (2011-2014).

Contract type	Female%	Male%	Difference %
Apprenticeship	3.8 %	5.2%	-1.4%
Projects Work Co.Co.Co.	5.3%	5.6%	-0.3%
Fixed term	57.1%	52.9%	4.2%
Open ended	18.5%	21.2%	-2.8%
Others	15.3%	15.1%	0.2%
Total	100 %	100%	

Table 4: Hires by contractual type and age, percentages (2011-2014).

Contract type	Age				
	up to 29	30-49	50 and over	Total (%)	Total (Count)
Apprenticeship	13.7%	0.3%	0%	4.4%	11472
Projects Work Co.Co.Co.	4.7%	5%	7.9%	5.4%	13956
Fixed term	45.3%	60.3%	57.5%	55.1%	142582
Open ended	14.7%	22.8%	19.9%	19.7%	51067
Others	21.6%	11.6%	14.7%	15.4%	39551
Total	100.0%	100.0%	100.0%	100.0%	258628

Table 5: Transition frequencies Job-to-Job

Contract type	Appr.	Project Co.Co.Co	Fixed term	Open ended	Others	Cens.	Total
Apprenticeship	31.69	0.57	8.09	7.71	4.48	47.45	100
Project work Co.Co.Co	1.66	43.43	11.36	3.28	4.79	34.67	100
Fixed term	1.01	0.64	56.94	10.98	3.89	26.27	100
Open ended	0.52	0.52	11.35	21.87	2.01	63.59	100
Others	3.22	1.97	20.50	4.27	35.84	31.45	100
Total	2.65	3.13	37.74	11.54	8.44	35.83	100

Contract type	Appr.	Project Co.Co.Co	Fixed term	Open ended	Others	Cens.	Total
Apprenticeship	53.04	0.80	0.95	2.96	1.92	5.88	4.44
Project work Co.Co.Co	3.38	74.95	1.62	1.53	3.06	5.22	5.40
Fixed term	21.08	11.33	83.18	52.44	25.39	40.43	55.13
Open ended	3.91	3.26	5.94	37.41	4.71	35.05	19.75
Others	18.58	9.66	8.31	5.66	64.92	13.42	15.29
Total	100	100	100	100	100	100	100

Table 6: Transition frequencies ALMP-to-Job.

Type of action	Appr.	Project co.co.co	Fixed term	Open ended	Other	ALMP	Cens.	Total
Literacy			6.90	0.86		92.24		100
Self proposed	3.54	2.28	24.25	5.12	5.59	59.21	1.73	100
Disadvantage			3.51	2.24	0.96	93.29	0.00	100
Vouchers						100.00	0.00	100
Training vouchers	0.11	0.44	2.14	0.25	0.67	96.39	1.19	100
New enterprise			40.00	14.29	2.86	42.86	5.71	100
Training	0.95	1.30	10.58	2.84	2.25	82.09	0.83	100
Placement	5.31	0.88	38.05	3.54	11.50	40.71	2.65	100
Education	14.81	0.93	26.85	6.48	14.81	36.11		100
Counceling	2.13	1.60	24.82	4.97	5.13	61.36	2.54	100
Income support	1.12	2.68	56.60	6.49	8.05	25.06	5.59	100
Internship	10.01	4.42	34.54	5.25	35.50	10.27	2.66	100

Table 7: ALMP-to-ALMP Transitions.

	Literacy	Self proposed	Disadvantage people	Vouchers assistance	Vouchers training	New enterprises	Training	…
Literacy	0.00	0.00	0.00	0.00	0.00	0.00	3.45	
Self proposed	0.00	6.86	1.17	0.00	8.44	0.00	0.08	
Disadvantage	0.00	0.00	1.31	0.33	13.07	0.00	0.65	
Vouchers (assistance)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Vouchers (training)	0.03	0.06	0.06	0.00	6.32	0.00	0.43	
New enterprises	0.00	0.00	0.00	0.00	0.00	0.00	17.14	
Training	1.13	0.12	0.00	0.00	0.65	0.00	0.47	
Placement	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Education	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Counceling	0.09	0.18	0.11	0.00	2.27	0.05	2.22	
Income support	0.00	0.22	0.22	0.00	2.25	0.00	0.00	
Stage Internship	0.00	0.13	0.00	0.00	1.07	0.00	0.10	

Table 8: ALMP-to-ALMP Transitions. Continued

	Placement	Education	Counceling	Income support	Stage Internship	Job	Censoring	Total
Literacy	1.72	1.72	81.03	0.00	4.31	7.76	0.00	100
Self proposed	0.17	0.00	36.71	0.00	1.42	43.31	1.84	100
Disadvantage	0.00	0.00	77.45	0.00	0.33	6.86	0.00	100
Vouchers (assistance)	0.00	0.00	100	0.00	0.00	0.00	0.00	100
Vouchers (training)	0.03	0.00	87.89	0.03	0.26	3.69	1.22	100
New enterprises	0.00	0.00	11.43	5.71	2.86	57.14	5.71	100
Training	0.47	0.41	72.69	0.53	4.74	17.95	0.83	100
Placement	0.00	0.00	21.43	1.79	14.29	59.82	2.68	100
Education	0.00	0.00	5.56	1.85	28.70	63.89	0.00	100
Counceling	0.12	0.18	27.73	0.64	6.47	56.25	3.70	100
Income support	0.00	0.00	7.87	0.67	7.87	75.28	5.62	100
Stage Internship	0.00	0.00	5.02	0.05	0.83	90.12	2.68	100

Table 9: Survivor functions at specific time points (months).

Time months	Survivor function	Confidence Interval Lower	Upper
1	0.948	0.947	0.950
2	0.908	0.906	0.909
3	0.903	0.901	0.905
6	0.886	0.884	0.888
12	0.854	0.852	0.856
24	0.769	0.766	0.772
36	0.701	0.697	0.704

Table 10: Cox regression model. CO-PES data.

Variable	Hazard Ratio	Robust Std. Errors Std. Errors	p-value
Age	1.006	0.001	0.000
Female	1.112	0.031	0.000
Fornero	0.805	0.047	0.000
N. Jobs	0.921	0.007	0.000
N. ALMPs	0.851	0.015	0.000
ALMP	1.369	0.101	0.000
Appr.	0.733	0.064	0.000
Fixed	1.285	0.049	0.000
Project	0.876	0.059	0.049
Training	1.047	0.261	0.853
High qualified	0.801	0.044	0.000
Low qualified	1.224	0.042	0.000
Log pseudo-lik	Wald chi2(12)	Prob > chi2	
-50824.84	570.29	0.0000	

Table 11: Cox regression model. CO-PES-EESI data.

Variable	Hazard Ratio	Robust Std. Errors	p-value
Age	1.002	0.005	0.641
Female	1.303	0.165	0.037
Fornero	0.860	0.207	0.531
N. Jobs	0.930	0.027	0.012
N. ALMPs	0.862	0.063	0.042
ALMP	1.422	0.367	0.173
Appr.	0.542	0.221	0.134
Fixed	1.043	0.167	0.791
Project	0.710	0.223	0.276
Training	0.541	0.401	0.407
High qualified	0.635	0.183	0.115
Low qualified	0.763	0.129	0.109
EESI	0.767	0.079	0.010
Income	1.003	0.000	0.000
H. Size	0.945	0.040	0.185
Log pseudo-lik	Wald chi2(15)	Prob > chi2	
-1793.3485	83.50	0.000	

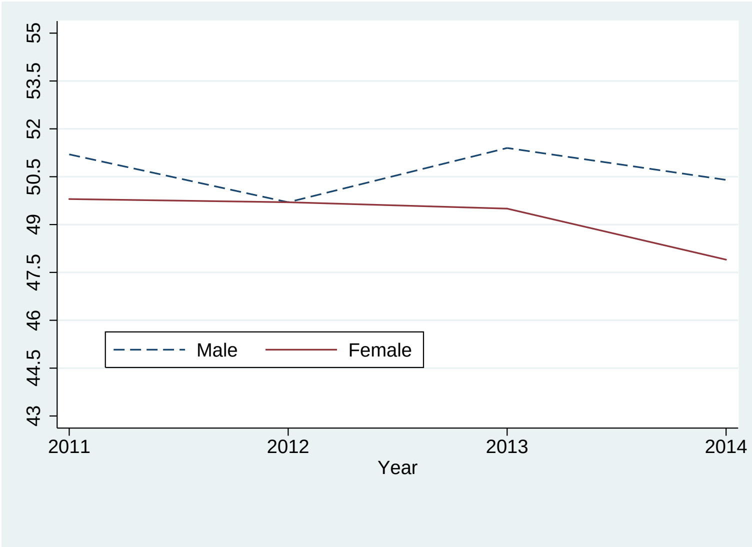

Figure 1: Contractual Quality Index by gender.

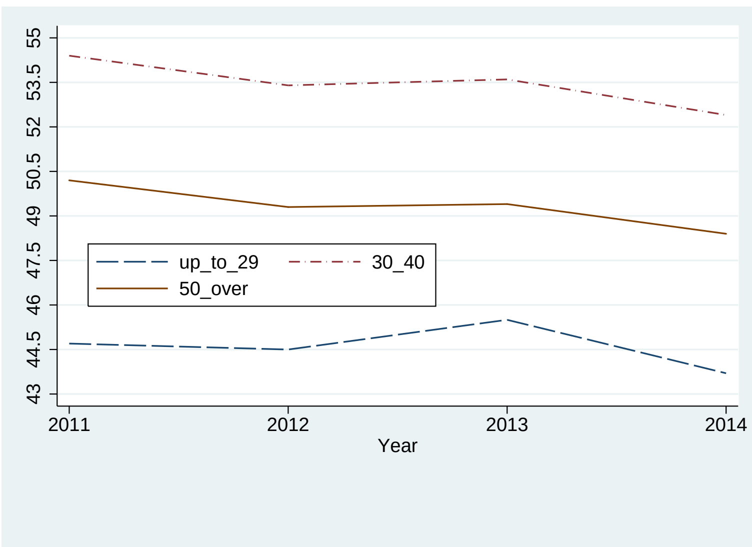

Figure 2: Contractual Quality Index by age group.

Figure 3: Total hires.

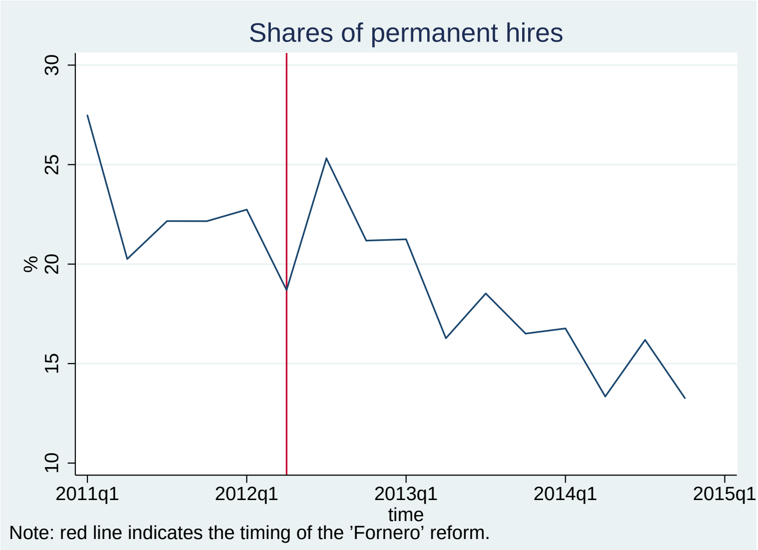

Figure 4: Share of permanent hires.

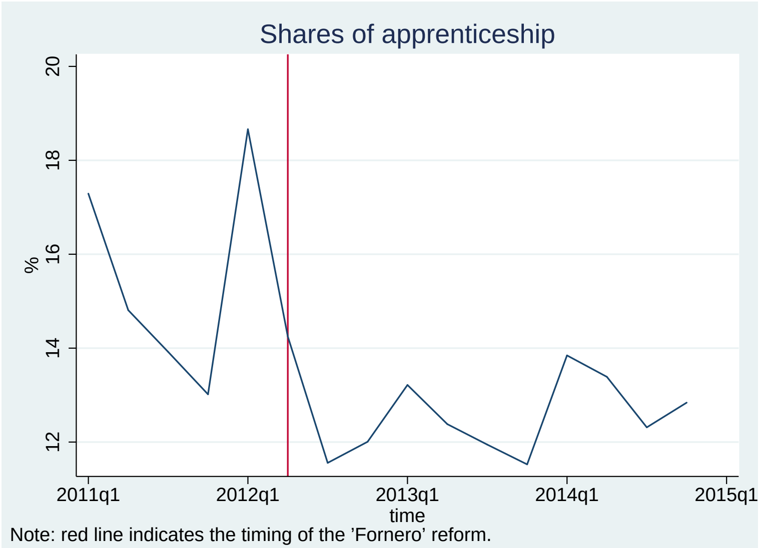

Figure 5: Share of apprenticeship contracts on total young hires (29 or younger).

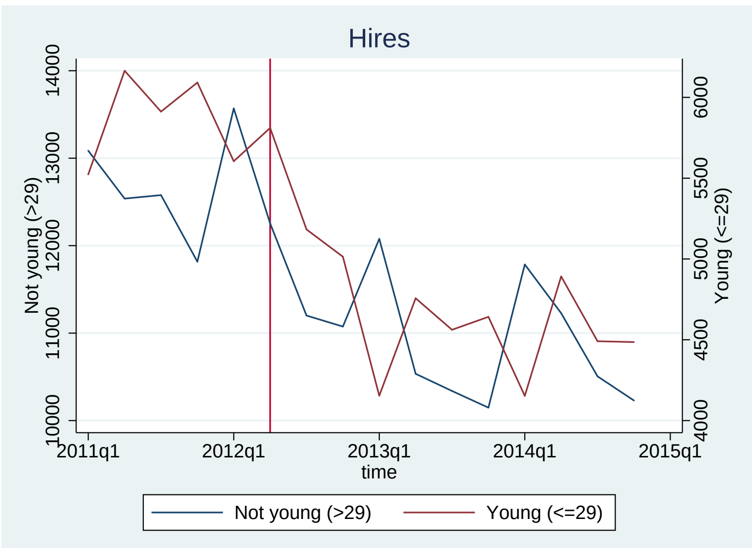

Figure 6: Number of young hires (29 or younger).