Young in-Old out: a new evaluation based on Generalized Propensity Score

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Abstract

This paper aims at evaluating the effect of the amount of older workers exits (aged 50 or more) on the entries of youngsters at a local labour market level, during years 1985 - 2002. If we can observe some effect of the exits on the entries, it will shed light on the substitution between older workers and youngsters. Moreover, since in our model the *causal agent* cannot be specified a – priori, we don't know *what causes what*. Hence, we are actually looking for a *correlation* between these two quantities. Systematic differences in background characteristics, between local markets with different levels of the older workers exits, can bias the effect estimation on the entries of youngsters. In order to adjust for this, we apply propensity score methods as extended and generalized in a setting with a continuous treatment by Hirano and Imbens (2004). Our results show a positive and significant correlation between exits of older workers and entries of youngsters.

Keywords: Synthetic firms, Evaluation, Non-experimental methods, Continuous treatment, Matching, Generalized propensity score, Dose-response function

JEL codes: C13, C49, J68

1 Introduction

Over the last three decades, the most of European countries experienced an ageing of their population along with a fall in employment rate among older workers. In the face of declining ratios of economically active to retired households, some countries increased their legal retirement age to balance the budget of their pay-as-you-go retirement schemes. However, the efficiency of such a policy option depends strongly on the impact of an increase in retirement age on job creation and employment among the younger cohorts of workers.

At first sight, we can think that an increase in legal retirement age, encouraging firms to maintain their aging workforce, could slowdown the dynamics of new hirings, if firms were expected to squeeze out their older workers and to replace them by new young workers. However, this simplistic idea has been severely criticized by recent papers. Cadiou et al. (2002) highlight the fact that the low probability to find a job for youngsters stems from their lack of experience. Consequently, they can not fill a job requiring more tenure in the firm. In this setting, youngsters and senior workers are not perfectly substitutable.

Even though the two sorts of jobs for the younger and the older generation differ greatly in the set of skill and experience requirements, a decrease in exits of older workers may have a negative impact on the hiring level of youngsters, through a vacancy-chain effect (Contini and Revelli, 1997). The idea is the following: if we consider within a local labour market[1], that the exit of an older worker implies a vacancy[2], there is a non-negative probability that it will be filled by an employed job seeker (attracted by better opportunities or higher wage) belonging to the same age group or to the previous age group. Therefore, it implies a new vacancy that can be filled by another younger employed job seeker, involving job-to-job flows that may result in hiring a young worker from out of the internal labour market.

Although substitutability between older workers and youngsters in the labour market appears to be a key point to better grasp the effect of an increase in retirement age, few papers address this issue empirically. In a macroeconomic perspective, using French data, Bozio (2006) investigates the effect of a variation in exits of older workers on hirings of youngsters, using financial incentives of the retirement decision as instrumental variables. He finds that over time an increase in exits of older workers is not correlated with the youth unemployment rate.

In a microeconomic perspective, Portugal et al. (2007) investigate the effect of the increase in legal retirement age for women on worker flows of different age groups, using detailed matched employer-employee Portuguese data. Their empirical methodology lies on a quasi-experiment given the fact that only women are affected by the retirement reform. Using a difference-in-difference matching method, they show that treated firms hire one to two fewer workers for each senior retained after the increase in legal retirement age and this decrease in job creation is particularly strong for younger workers.

In this paper we investigate the correlation between the exits of older workers on hirings of youngsters, in the light of the vacancy-chain theory, using Italian matched employer-employee data. Consequently, we do not consider firms but rather local labour markets, to account for job-to-job flows. Using propensity score matching methods

[1] Here we refer to as "local labour market" a set of firms of a given sector and in a given geographical area, and whose jobs have the same skill level (white collar or blue collar workers)
[2] It is the case if there is no employment contraction

generalized in a setting with a continuous treatment (Hirano and Imbens, 2004), we find a strong positive correlation between net exits of older workers and net entries of youngsters.

This article is organized in the following way: in section 2 we explain our empirical methodology, in section 3, we describe the type of data used and finally, in section 4 and 5 we report the results and conclusions.

2 Causal agent and methodology

Actually, in our model, the *causal agent* cannot be specified a – priori, that is:
- we can observe old exits followed by young entries
- (but also) we can first have young entries that cause old exits.

We can say, we don't know *what causes what*.
In fact, since we want to investigate the *substitution* between young and old workers, in terms of entries of the former and exits of the latter, we can have different *causal processes*. For example, we can observe:

- entries of youngsters - because they are more convenient in terms of salary - that imply exits for elders
- exits of elders, that imply *vacancies* available for young workers

In both situations, young and old workers need to be perfect substitutes. As a consequence, we are looking for a *correlation* between these two quantities and it is arbitrary the identification of the outcome Y as well as of the treatment variable (that is, entries or exits can respectively be the treatment and the outcome or the inverse).

Moreover, if they are substitutes, we don't know *a-priori* the temporal sequence of the events. So, in the same year, we can observe:

- entries of young and, only later, exits of old
  (because firms need to train the new entry, before the exit of the old workers)
- contemporary entries of young and exits of older people…

In other words, our null hypothesis is no-correlation between young and old workers within synthetic firms, that we can instead find at a labour market level, because of, for example, the entry of new enterprises who can hire new young workers.

Anyway, we decided to set the variation in exits of older workers, between year t and the year (t+1), as the treatment variable, evaluating the effect of the net exits on the net entries of youngsters, during years 1987 - 2002. In particular, we consider waves of three years, starting from 1989 until 2002. Using the potential outcome approach to causal inference (Rubin, 1974, 1978), we estimate a continuous dose-response function that relates each value of the dose, i.e., net elders' exits, to the net youngsters' entries, at a labour market level. Formally, consider a set of N local labour markets, and denote each of them by subscript i: $i \in \{1, ..., N\}$. For each local markets i, we observe a vector of pre-treatment variables, X_i, the net older workers' exits, T_i, and the value of the outcome variable associated with this 'treatment level', $Y_i = Y_i(T_i)$, with Y_i represented by the net younger workers' entries. As in the binary treatment context, propensity scores methods in a setting with continuous treatments rely heavily on the key assumption that adjusting for pre-treatment differences solve the problem of drawing causal inference. Formally, we make the weak unconfoundedness assumption, introduced by Hirano and Imbens (2004), which requires that the treatment assignment mechanism is conditional independent of each potential outcome given the pre-treatment variables:

$$Y_i(t) \perp T_i | X_i \text{ for all } t \in \mathcal{T}$$

assuming that $\{Y_i(t)\}_{t\in T}$, T_i, and X_i, i = 1, ..., N are defined on a common probability space, that T_i is continuously distributed with respect to Lebesgue measure on $\mathcal{T}$, and that $Y_i = Y_i(T_i)$ is a well defined random variable. Given unconfoundedness, we can apply matching methods based on the Generalized Propensity Score (GPS) with continuous treatments introduced by Imbens and Hirano (2004). The GPS is defined as the conditional density of the actual treatment given the observed covariates. Formally, let $r(t, x) = f_{T|X}(t|x)$ be the conditional density of the treatment given the covariates. Then, the GPS is $R_i = r(T_i,X_i)$. The GPS is a balancing score, that is, within strata with the same value of $r(t, x)$, the probability that $T = t$ does not depend on the value of X. In combination with the weak unconfoundedness assumption, this balancing property implies that for every $t\in \mathcal{T}$

$$f_T(t|r(t, X_i), Y_i(t)) = f_T(t|r(t, X_i)).$$

As a result, the GPS can be used to eliminate any biases associated with differences in the covariates. Formally, if the assignment to the treatment is weakly unconfounded, given pre-treatment variables X_i, then

$$\mu(t, r) = \mathrm{E}[Y_i(t)|r(t,X_i) = r] = \mathrm{E}\,[Y_i\,|T_i = t, R_i = r] \quad \text{and} \quad \mu(t) = \mathrm{E}\,[\mu(t, r(t,X_i))].$$

The GPS methods are implemented in our application using the gpscore, dose-response STATA package (Bia & Mattei, 2008). A key assumption in the STATA implemented version of the GPS methods is the normality of the treatment variable conditional on the pre-treatment covariates. In our application we assume that the Box – Cox transformation of the treatment (amount of elders' exit) has a Normal distribution, given the covariates. Formally, let *BoxCox*(T_i) denote the *Box Cox* transformation of the treatment variable:

$$BoxCox(T_i) = \begin{cases} \dfrac{T_i^{\lambda-1}}{\lambda} & if \quad \lambda > 0 \\ \log(T_i) & if \quad \lambda = 0 \end{cases}$$

Then, we assume that $BoxCox(T_i)\,|\,\mathrm{X}_i \sim \mathrm{N}(b_0 + b_1\,\mathrm{X}_i\,, \sigma^2\,)$[3]

3 Data

In our elaboration we use the Worker Histories Italian Panel (WHIP), a database of individual work histories, based on Inps administrative data. The reference population is made up by all the people – Italian and foreign – who have worked in Italy even only for only a part of their working career. The WHIP section concerning employee contracts is *a Linked Employer Employee Database*: in addition to the data about the contract, thanks to a linkage with the Inps Firm Observatory, data concerning the firm in which the worker is employed is also available.

Nevertheless, the available firm sample is *worker-based*. As a consequence the archives supplied by Inps concern neither the firms population nor a random sample. Since we are interested in the correlation between entries of young workers and exits of old workers, to avoid the problem of a non representative sample of enterprises, we decided to adopt a *synthetic firms* approach, pooling together firms observed in a certain *province* and *sector*. So, the statistic unit is now the combination between these two variables, inducing to investigate

[3] The parameter λ, which the Box – Cox transformation depends on, is estimated from the data.

the eventual substitution between old and young workers, we can say, at a *local labour market level*.

We can have a discussion about this approach. Indeed, it may lead us to misestimate the worker flows in our economy, with respect to a firm-level analysis. To test the accuracy of this method, Contini et al. (2008) investigated wage mobility and dynamics in Veneto region, comparing the results obtained by using synthetic firms approach with those resulting from a firm-level analysis. They found similar result, even though the first approach tend to overestimate the within firm mobility and to underestimate the between firms mobility. However, they show that this problem decreases if we decrease the size of the cell. So there is a trade-off in the choice of the disaggregating level, between having the finest grid, and having a sufficient number of observations in each cell.

Furthermore, studying the worker mobility within a local labour market allows us to account for the job to job flows. In Italy, during the period of interest, these type of flows represent the major part of the observed flows as shown by Leombruni and Quaranta (2005). They show that these flows are observed almost only within an activity sector, in other words, the inter-sectorial mobility is very weak. Furthermore, investigating the geographical worker mobility, they observe that it represents a small part of the worker flows, so inter-area mobility is also very weak. Therefore when defining a local labour market, we can control for all the worker flows, induced by the variation in separation rate of older workers, through the phenomena of vacancy-chain. Hence, we organized the data by province and sector, getting about 800 cells[4] by wave.

To satisfy the unconfoundedness assumption we consider pre-treatment variables likely to have an impact on elders' exits and youngsters' entries. First we consider the gender structure of the local labour market, namely the share of women observed for each statistic unit. We also control for the age structure of each labour market, considering the share of workers aged less than 30 and the share of workers aged 50 or more.

Regarding the youngsters, to isolate the effect of the introduction of the CFL contracts on the young workers' entries, we control for the share of young employed with this type of contract for each statistic unit. We also introduce as pre-treatment variable the ratio between the wages of young and older workers. Indeed, this gap may have some impact on the substitutability between these two cohorts of workers. Furthermore, this substitutability may also be affected by the average skill level within each local labour market. Hence we control for the share of blue collar employees for each statistic unit.

Drawing on previous studies of Contini et al. (2002) it appears that the age and the size of firms have a strong impact on worker mobility. Consequently, we consider as pre-treatment variable the share of young enterprises (less than 8 years) and the share of small firms (less than 9 workers). To control for the differences in economic situation between local labour markets, we consider as pre-treatment variables the unemployment rate within each cell. Finally, to control for a simple size effect, we introduce the variable entitled "occupational level" namely the number of employees by province and sector. All these pre-treatment variables are considered at time (t - 1) and (t - 2).

As already underlined, we want to estimate the effect of the old exits on the young entries, in a dynamic setting, within waves of three years. So, for example, starting from 1989, we set the "treatment period" in that year, considering as pre-treatment variables the values of all covariates in 1988 and 1987. Then, we step one year forward, getting a new wave, where now the treatment period is 1990 and the all pre-treatment variables are set in the two previous

[4] That is, 800 different combinations of province and sector.

years (1989, 1988). We make this until 2002, getting a total of 14 waves to investigate. Moreover, we also introduced job creation (named jc-t_2) and job destruction (named jd-t_2) as control variable at time *t*. We made this choice because we can reasonably suppose a strong correlation between the amount of the old workers exits and the youngsters' entries with these two quantities, just in the same period. In fact, it is plausible to think that a higher level of job-creation, just after, induce higher probabilities of being hired as well as a lower level of job destruction.

4 Results

To be effective, matching should balance characteristics across the treatment groups, The extent to which this has been achieved can be explored by comparing balance in the pre-treatment covariates before and after adjusting for the estimated GPS. For each of the covariates, we investigate the balance by testing whether the mean in each treatment interval is different from the mean in the other ones. Table 1, in Appendix, provides the unadjusted and GPS – adjusted mean differences and the Bayes - Factor Test statistics[5] for equality of means, considering three intervals of elders' exit: [0.4, 1.3), [1.3, 2.6) and [2.6, 13). Adjusting for the GPS seems to improve the balance, above all when the unadjusted differences are high. As an example, consider the variables entry and occupational level, at time t_0 (but also at time t_1).The mean difference between treatment group, number of elders'exits , [0.4, 1.3) and the other ones is 5.2 (SE = 1.044) for the former and 120.2 (SE = 15.8) for the latter. After adjusting for the GPS these differences dropped to 3.5 (SE =1.2), and 76.5 (SE= 17.7), respectively.

In order to estimate[6] the effect of exits on entries (we could also say: find correlation between exits and entries), we first need to compute the conditional expectation of the outcome, $E[Y \mid T = t, R = r]$, that is equal to:

$$\mathrm{E}[Y \mid T = t, R = r]=\mathrm{E}[Y(t) \mid r(t,X) = r]= \beta\ (t, r)$$

and estimated as a function of a specific level of treatment and of a specific value of GPS $R = r$. Hence, average the conditional expectation over the marginal distribution $r(t,X)$:

$$\mu(t) = \mathrm{E}[\mathrm{E}[Y(t) \mid r(t,X)\ ]]$$

to estimate the *causal effect* as a comparison of $\mu(t)$ for different values of *t*. First of all, we estimate the GPS, verifying the most suitable specification of the conditional distribution of the treatment given covariates and investigating if the GPS satisfies the balancing property, wave by wave.

In our application we specify a *linear approximation* in the model, in order to estimate the level of young entries given $T = t$ and the *pscore*:

$$E[y, r] = b_0 + b_1 t + b_2 pscore + b_3\ t{*}pscore$$

So, we estimate the outcome, young entries, as a mean weighted by each different pscore, predicted in correspondence of all specific level of exits we are interested in.

$$\hat{\mu}(t) = \hat{E}(Y) = \frac{1}{N}\sum_{i=1}^{N} \hat{b}_0 + \hat{b}_1\, t + \hat{b}_2\ ps\hat{c}ore + \hat{b}_3\ ps\hat{c}ore * t$$

[5] Bayes factors are interpreted following Jeffrey (1969). Let B_{01} denote the Bayes Factor for nested models $M_0 \subset M_1$, then $B_{01} > 1$: evidence supports M_0; $1 > B_{01} > 10^{-0.5}$: very slight against M_0; $10^{-0.5} > B_{01} > 10^{-1}$: moderate against M_0; $10^{-1} > B_{01} > 10^{-2}$:strong to very strong against M_0; $10^{-2} > B_{01}$:decisive against M_0;

[6] All the estimates are derived introducing the cluster option in the dose-response command (that is: controlling for province and sector)

Here we reported 3 graphs. In the first one we consider the confidence interval for difference between the outcome in t = 1and the outcome corresponding to an increase of the treatment equals to 1:

$$u(t + \Delta t) - \mu(t), \text{ with } \Delta t = 1$$

that we can interpret as *a causal effect*. Hence, the results, reported in *Graph 1*, show what would be the variation of young workers' entries, if the elders' exits increased from 1 to 2, over time. In this case, we have that one more elder's exit corresponds to more than one (+ 1,5) young workers' entry in 1989. We find a recession during 1990 and 1993, with (about) a null variation in youngsters' entries in correspondence of 1 more elder's exit, while, between 1995 and 2000, this difference hovers about 1 more young worker's entry. In 2002 the effect of one more old worker's exit is the highest one and equals to (about) 2 more young workers.

Moreover, the estimates (in terms of difference) we got result to be very significant over the time (except for the years 1991, 1993). In *Graph 2*, we reported the dose-response function and the treatment effect function in correspondence of different values of elders' exits, during 1996. We can note how 1 more exit always corresponds to one more entry of young workers (for all the treatment values). Moreover, we got very significant estimates in terms of variation of youngsters' entries for all the elders' exits considered. In *Graph 3* we reported the dose-response function and the treatment effect function in correspondence of different values of elders' exits, during 1997. We can note how 1 more exit in t=1, corresponds to one more entry of young workers, while we would find 1,5 more youngster entry if we had 1 more exit in correspondence of t=2. Concerning the other variations in terms of youngsters' entries, this difference tends to decrease. Moreover, the treatment effect estimates got in correspondence of 1, 2, …4 elders' exits result to be very significant.

5 Conclusions

In this article we try to evaluate the effect of the amount of older workers net exits (aged 50 or more) on the net entry of youngsters at a local labour market level, during years 1985 - 2002.

In order to avoid the problem of a non representative sample of enterprises and to account for job-to-job flows, we decide to adopt a synthetic firms approach, pooling together firms observed in a certain province and sector, using the work histories Italian panel (WHIP) of administrative source. We estimate the dose – response functions and the effect of the amount of elders' exits on youngsters' entries, applying propensity score methods, as extended and generalized in a setting with a continuous treatment by Hirano and Imbens (2004). Our results show a positive and significant correlation (except for the years 1991, 1993) between net exits of older workers and net entry of youngsters. In particular, we find that the variation of youngsters, given an increase of the elders' exits from 1 to 2, is on average equal to more than one young workers' entry, with the highest value equals to (about) 2 in 2002.

There are two main directions for future research. The first is to extend this study identifying the outcome Y with the elders' exits and choosing as treatment variable the youngsters' entries, since, as already underlined, we are looking for a *correlation* between these two quantities and it is arbitrary the identification of the outcome as well as of the treatment variable. Secondly, it could be of considerable interest to investigate the substitution between blue collars and white collars, for example, in terms of entries of the former and exits of the latter, highlighting, in this way, an eventual correlation between these two variables, conditional to the workers' status. Finally, we could also analyze the robustness of our results with respect to the underlying identifying assumptions, through appropriate sensitivity analyses.

APPENDIX

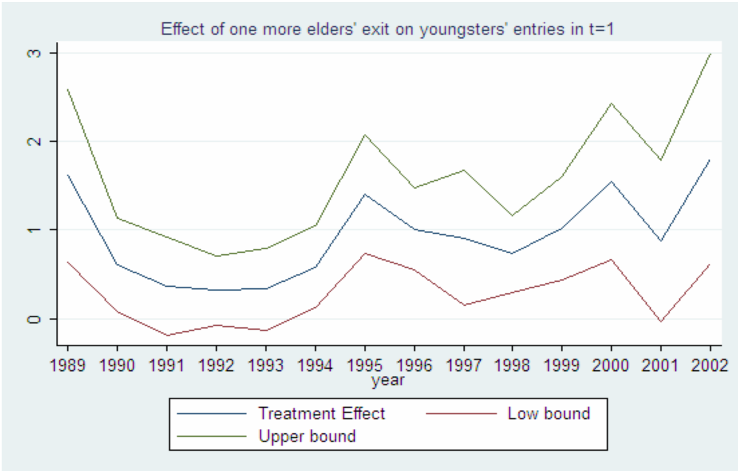
Table 1 Synthetic firms: balance given the generalized propensity score (year 1989)
Mean Difference (MD) (Standard error, SE, in parenthesis) and Bayes Factor statistics for equality of means

Treatment interval	[0.4; 1,3)				[1,3; 2.61)				[2,61; 13)			
	Unadjusted		GPS -Adjusted		Unadjusted		GPS -Adjusted		Unadjusted		GPS -Adjusted	
Variables	MD (SE)	BF	MD	BF	MD (SE)	BF	MD (SE)	BF	MD (SE)	BF	MD (SE)	BF
share foreigners t_1	.0005	13.77	.007	1.5919	-.003	9.03	-.004	3.78	.002	10.45	.002	7.22
	(.003)	.	(.004)		(.003)		(.004)		(.003)		.004	
share youngsters t_1	.0432	.537	.026	3.124	-.001	12.89	.006	6.86	-.047	.39	-.025	3.77
	(.0169)		(.018)		(.018)		(.019)		(.018)		(.020)	
share elders t_1	.004	12.57	-.005	6.8216	-.010	5.97	-.012	2.23	.010	9.91	.010	4.22
	.(007)		(.008)		(.008)		(.008)		(.008)		(.009)	
share young firms t_1	.038	1.51	-.002	8.4144	.011	10.73	.030	2.27	-.054	.218	-.046	.897
	(.018)		(.019)		(.019)		(.020)		(.019)		(.021)	
share female t_1	.058	.196	.051	.66364	-.016	9.51	-.011	6.45	-.049	.861	-.012	7.31
	(.019)		(.022)		(.021)		(.023)		(.021)		(.025)	
share blue collar t_1	-.020	12.36	-.025	4.9499	.038	3.44	.024	4.37	-.025	7.26	-.013	7.27
	(.021)		(.024)		(.023)		(.024)		(.023)		(.027)	
share small firms t_1	.058	1.04	.008	8.0992	.003	12.89	.037	3.08	-.070	.564	-.073	.553
	(.025)		(.028)		(.027)		(.028)		(.027)		(.031)	
ratio youngsters training contracts t_1	.017	9.57	.001	8.4507	.010	11.54	.006	6.98	-.029	4.92	-.023	5.33
	(.019)		(.022)		(.021)		(.022)		(.020)		(.025)	
entry t_0	**5.27**	6.0e-05	3.56	.11298	**2.44**	1.39	1.62	3.27	**-8.39**	4.0e-12	-4.44	.016
	(1.044)		(1.204)		(1.15)		(1.28)		(1.06)		(1.24)	
occupational level t_0	**120.23**	2.8e-11	76.58	.00115	**41.99**	.919	39.96	1.10	**-178.01**	5.8e-24	-75.32	.0003
	(15.81)		(17.74)		(18.24)		(20.54)		(15.55)		(16.28)	
share foreigners t_0	.0007	13.58	.006	1.9737	-.003	9.91	-.003	5.12	.001	11.66	.0006	8.15
	(.003)		(.003)		(.003)		(.003)		(.003)		(.004)	
share youngsters t_0	.051	.152	.023	3.7582	-.005	12.30	.006	6.90	-.053	.198	-.026	3.75
	(.017)		(.018)		(.018)		(.019)		(.018)		(.021)	
share elders t_0	.005	11.24	-.005	6.5897	-.008	7.34	-.007	5.13	.002	12.28	.004	7.22
	(.007)		(.008)		(.008)		(.008)		(.008)		(.009)	

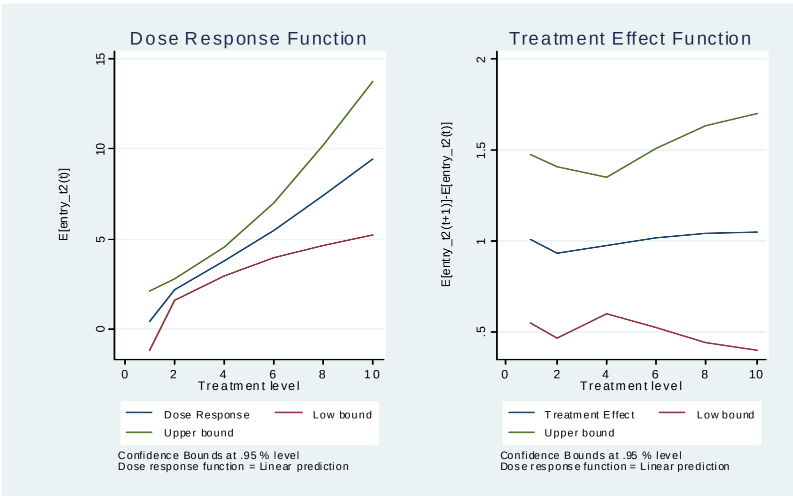
share young firms t_0	.042	.921	-.002	8.4019	.004	12.64	.029	2.60	-.052	.341	-.044	1.18
	(.018)		(.020		(.019)		(.020)		(.019)		(.022)	
share female t_0	.058	.185	.052	.643	-.015	10.09	-.010	6.63	-.052	.679	-.011	7.37
	(.019)		(.022)		(.021)		(.023)		(.021)		(.025)	
share blue collar t_0	-.006	13.41	-.025	5.03	.036	3.76	.026	4.02	-.029	5.93	-.020	6.27
	(.021)		(.024)		(.023)		(.024)		(.023)		(.027)	
share small firms t_0	.061	.840	.006	8.22	-.003	12.84	.035	3.46	-.066	.704	-.069	.781
	(.025)		(.028)		(.027)		(.028)		(.027)		(.031)	
ratio youngsters training contracts t_0	-.012	10.23	-.003	8.31	.024	4.61	.015	5.21	-.010	11.05	-.016	6.004
	(.015)		(.018)		(.016)		(.018)		(.016)		(.020)	
entry t_1	**5.69**	3.7e-05	3.26	.316	**3.04**	.604	2.93	.75	**-9.46**	6.9e-14	-4.64	.0108
	(1.10)		(1.26)		(1.22)		(1.37)		(1.11)		(1.25)	
occupational level t_1	**123.37**	2.3e-11	78.78	.001	**41.54**	1.09	39.77	1.22	**-181.14**	1.2e-23	-77.92	.0002
	(16.16)		(18.15)		(18.67)		(21.04)		(15.94)		(16.78)	
job creation t_2	3.23	.025	2.61	.425	1.14	6.62	.900	5.27	-4.79	5.3e-05	-2.67	.463
	(.904)		(1.06)		(.991)		(1.12)		(.949)		(1.11)	
Job destruction t_2	1.03	.036	.366	4.77	.322	7.89	.260	5.66	-1.48	.0002	-.266	6.07
	(.297)		(.344)		(.325)		(.366)		(.312)		(.343)	
unemployment rate t_0	-.012	1.78	-.011	2.27	.002	11.73	.002	6.83	.011	2.93	.004	6.96
	(.006)		(.007)		(.006)		(.007)		(.006)		(.007)	
unemployment rate t_1	-.012	2.99	-.011	3.31	-.005	12.91	.0008	7.27	.014	2.06	.004	7.22
	(.007)		(.008)		(.007)		(.008)		(.007)		(.009)	
ratio youngsters elders income t_0	-.004	13.59	-.047	3.27	-.032	9.45	.022	6.03	.037	8.60	.012	7.86
	(.039)		(.034)		(.042)		(.036)		(.041)		(.040)	
ratio youngsters elders income t_1	.050	4.23	-.029	6.00	-.009	12.33	.026	5.69	-.047	5.11	-.050	3.98
	(.032)		(.036)		(.035)		(.037)		(.034)		(.042)	

Minimum bayes factor =.00028006 < 0.01

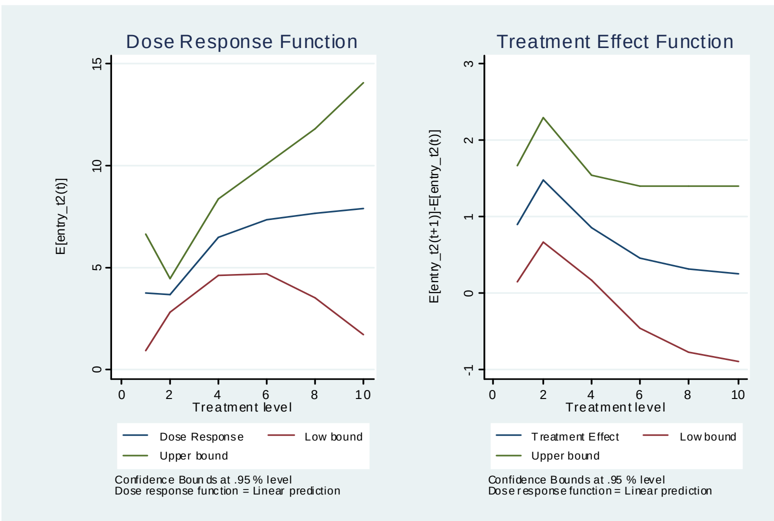
Graph 1 $u(t+1) - \mu(t)$ and confidence bands 95% in $t = 1$ over the time



Graph 2 $u(t+1) - u(t)$ and confidence bands 95% (1996) in t = 1, t = 2,…, t = 6



Graph 3 $u(t+1) - u(t)$ and confidence bands 95% (1997) in t = 1, t = 2…, t = 6



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