Generation Internship - The Impact of Internships on Early Labour Market Performance

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Abstract

Many university graduates conduct internships before starting to work in a direct-hire job. I analyse the effects of internships on early labour market performance to evaluate whether they enhance the university-to-work transition. I use propensity score matching to identify graduates that resemble each other in important characteristics such as cognitive ability, and only differ with respect to the internship experience. This allows comparisons between interns and non-interns in key indicators for job market performance: monthly earnings, employment status, and job satisfaction. The results suggest that internships have detrimental effects on all three dimensions. Graduates with an internship experience earn significantly less than their non-intern peers, and are less likely to be employed within one year of graduation. However, the negative effects are short-lived and vanish within five years.

JEL classification: J31, J24, J22

Keywords: internships, temporary work, propensity score matching, youth employment, job-shopping

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1 Introduction

In recent years, a university degree alone does no longer seem to be enough to find a permanent job, even though it is thought to be a key ingredient to labour market success. Ever more often, university graduates go through short-term practical work experiences, e.g. internships, before finding regular employment. The public press likes referring to this phenomenon as the emergence of the *Generation Internship*. Indeed, in Germany and Italy, internship take up rates among university graduates were as high as 11 and 25% in 2005. Interns can be found among graduates from most fields of study - from the arts to the hard sciences alike. Although they are heavily promoted by many universities, and have received a lot of attention in the press, their effects for subsequent job market success have never been thoroughly analyzed. Therefore, the goal of this study is to understand the effects of internships on labour market dynamics. Understanding this emerging phenomenon is particualrly important to potentially target policies towards their promotion or discouragement.

My main research question is whether internships are effective stepping-stones into regular work. More specifically, I analyse whether university graduates with an internship experience are more likely to be employed within one year after graduation, and how their employment status evolves up to five years thereafter. Moreover, I evaluate whether interns find better jobs in terms of monthly earnings, and work satisfaction, or whether internships trigger negative effects.

Throughout this study, internships are characterized as short-term professional work experiences. They typically last only a few months, and should serve an educational scope. Internships are poorly remunerated, if not completely unpaid. From a conceptual point of view, an internship may increase the chances of finding regular work due to several factors. Clearly, they may be seen as work experience and enhance human capital accumulation (Mincer, 1962). They could provide a screening device for employers to test a new worker (Stigler, 1962). Also, employers could save on social benefits before hiring the intern on a regular contract. Graduates may also benefit from internships if they help signalling motivation, as well as effort to potential employers. Furthermore, interns may wish to gain on-the-job experience to increase their employability through specialization and networking. Nevertheless, internships might also trigger adverse effects. Potential employers could perceive the internship as a negative signal because no direct-hire job was found straight away. Such signals would lead employers to believe that interns are a negative selection among all graduates (Akerlof, 1970; Greenwald, 1986). Finally, there may be locking-in effects (Van Ours, 2004). Job-search intensity is typically reduced during an internship, which decreases the probability of finding a direct-hire job (García-Pérez and Muñoz-Bullón, 2011; Gagliarducci, 2005), and one should not neglect the risk of being labelled as an eternal intern after a certain number of internships.

To my best knowledge no other research has yet looked at how internships may impact the transition into regular employment. Existing studies on the school-to-work transition concentrate on duration until graduates find work, on job satisfaction, as well as on over-education, and job-mismatch (Biggeri et al., 2001; Salas-Velasco, 2007; OECD, 2011; Espa et al., 2007; Marzano and Palidda, 2011). Oreopoulos et al. (2012) elucidate the effects of transitioning during an economic downturn. Van der Klaauw and van Vuuren (2010) analyze the tradeoff between the benefits of intensified job search towards graduation and study efforts leading to higher academic attainment. They conclude that the two strategies are close substitutes.

In parallel to my analyses, numerous studies have investigated the role of temporary jobs and fixed-term contracts for the transition from unemployment into regular employment. Much evidence is in favor of the stepping-stone hypothesis (Jovanovic and Nyarko, 1997; Autor and Houseman, 2010; Booth et al., 2002; de Graaf-Zijl et al., 2011; Van den Berg et al., 2002). Although long-term effects on employment stability and wage trajectories remain ambiguous, the literature widely agrees that temporary jobs may accelerate transitions into employment, and substitute unemployment spells. Internships could trigger similar effects. Previous studies mostly looked at the performance of low-skilled workers and those belonging to minorities because of their particular risk of long-term unemployment. However, the same risk concerns young workers (Cockx and Picchio, 2012, 2013; Ryan, 2001). Higher education generally increases employment possibilities and decreases the risk of unemployment. Nevertheless, in most European countries, youth unemployment still exceeds average unemployment among the general adult population (OECD, 1998, 2012). The situation of young workers is particularly worrisome in Southern Europe (García-Pérez and Muñoz-Bullón, 2011; Dolado et al., 2002; Lilla and Staffolani, 2012) where unemployment rates are soaring, especially since the recent economic crisis (OECD, 2012). In Northern Europe on the other hand transitions go rather smoothly (Ryan, 2001; von Wachter and Bender, 2006).

To answer my research questions, I analyse survey data from the 2004/2010 graduate panels in Germany and Italy. The panels survey university graduates after approximately one, and three to five years of graduation. The surveys include extensive questions on the university-to-work transition, including, among others, information on employment, earnings, work and life satisfaction, and also on internships. Analysing data from Germany and Italy is particularly interesting in light of their important institutional and cultural differences, while at the same time being among the largest economies in Europe.

I use post-graduation internship experience as a treatment, and look at graduates with and without such an experience to compare their post-internship employment status, earnings, earnings trajectories, and job satisfaction. The main challenge of my analysis is self-selection into the treatment group. It is possible that the most able students are more prone to find a direct-hire job, or that those who readily find an internship could have also easily found a regular job. Wage trajectories may differ inherently due to personal characteristics, other than the internship. I therefore cannot assume random treatment assignment, and cannot claim causality of the reported effects. However, given the extensive data provided in the panels, I assume selection on observables, and use propensity score matching for treatment effect estimation (Rosenbaum and Rubin, 1983). I match individuals with equivalent university degrees, and similar cognitive, as well as non-cognitive capacities. These factors are believed to be important determinants of both academic and labour market success (Heckman and Rubinstein, 2001; Heckman et al., 2006). I show for both countries that interns and non-interns do not differ in observable characteristics, especially not in cognitive ability. Despite the observable similarities of interns and non-interns, their early labour market performances differ importantly. My results point towards detrimental effects of internships on the probability of finding employment, as well as on post-internship earnings, and work satisfaction. I find that interns in both countries under-perform their non-intern peers. Interns are less likely to be employed within one year of graduation and even if they find paid work, they receive significantly lower monthly earnings. In Germany the gap in monthly starting earnings is as large as 20-40%, whereas in Italy this earnings gap is much smaller, but still significant at -2.7%. The employment and earnings gaps decrease over time, and I observe a full catch up within five years of graduation in both countries. In addition to the adverse effects on employment and earnings, the effects on work and life satisfaction are less pronounced but remain negative as well. Interns are especially discontent with their job security and working hours.

The paper proceeds as follows. Section 2 describes the data. Section 3 defines internships and presents descriptive statistics. Section 4 discusses the conceptual background, and theories that might predict the effects of internships. The estimation strategy and results are found in Section 5, followed by a discussion in Section 6. Section 7 concludes.

2 Data

I use graduate panels from the DZHW in Germany and Almalaurea in Italy. These institutions are publicly funded non-profit organizations with the scope of collecting and providing data on the higher education system. The DZHW starts new panel waves roughly every 4 years. They survey a representative sample of German university graduates 1, 5, and 10 years after their final university examination. Starting with the wave of graduates from the academic year 2004/05 the survey includes details on post-graduation internships. I therefore use the first and second waves from this particular panel for my analysis. The first wave contains 11,783 observations. 5,327 observations are lost due to non-response to the second wave. The final German data set contains 6,456 observations. Almalaurea collects administrative data on all graduates of affiliated Italian universities.[1] For the sake of comparability I also use the 2005 panel for Italy. The Italian data contains administrative and interview data for 77,441 graduates.[2] However, only 26,344 respond to all three waves and 10,672 graduates report earnings for all waves.[3] Despite the important number of missing observations, there are no evident patterns of attrition bias. Randomization checks between the full and the selected samples do not show anomalies in important factors such as age, gender, university grades and internship participation.[4] In the following, I will conduct all main analyses in parallel for both countries. However, some in depth analyses will focus on Germany alone which is entirely due to data availability.

[1] In 2005, 43 out of roughly 70 public universities were affiliated with Almalaurea. The Almalaurea data is thus not representative of all Italian graduates but merely of the affiliated institutions.

[2] This corresponds to a response rate of 86% of all Almalaurea graduates.

[3] The rapid decline of the number of observations in the Italian data is especially due to an exclusion restriction of Bachelor graduates, that pursue their studies with a Master's degree. These bachelor graduates are no longer contacted for further waves, and let the number of observations drop by almost 45,000. For more information see Section 4.1.

[4] See Tables A1 and A2 in the Appendix for descriptive statistics between the selected sample and deleted individuals.

3 Descriptive Statistics

Throughout this research, internships are characterized as short-term, ideally supervised, professional work experiences. Internships should have an educational scope, and temporary character. Apart from a few exceptions, interns do not have a work contract, and are thus not protected within a legal frame. Internships are mostly poorly remunerated, if not completely unpaid.[5] I restrict my analysis to internships which are done after graduation, as opposed to internships which are completed during the course of studies.[6]

Table 1 shows descriptive statistics for interns and non-interns and indicates that the two groups resemble each other in key characteristics. Interns and non-interns are of same age, have similar study durations and attain the same mean grades at graduation. The only noticeable difference is that women appear to slightly overpopulate the group of interns, in both coutries: roughly 60% of non-interns, but around 65% of the interns are women.[7] Internships in the transition from university to work are indeed quite common. Roughly 11% of all graduates do an internship in Germany, and in Italy this share even amounts to 27%. Table 1 also shows enrolment in particular study fields by intern status. One notices that internships are common across all fields. Enrolment in a certain field of studies is largely independent of the later choice to do an internship. Internships are more frequent in fields where the labour market opportunities are less clear cut such as psychology and culture. 2% of non-interns in the German sample graduate from psychology but 5% of interns, in Italy these rates amount to 2.2% and 16.3% respectively. However, still a large amount of graduates, also go for an internship

[5] Unfortunately, questions about internship pay are not part of the data.

[6] The Italian data only contains information of post-graduation internships. In the German sample 1014 individuals report an internship experience. 288 among them did their internship during a second study program, or during a gap year. I do not consider these individuals as interns, because such internships may trigger much different effects than internships after graduation. See Saniter and Siedler (2014) for a recent paper on the effects of summer and gap year internships on labour market outcomes.

[7] See Tables A1 and A2 in the Appendix for augmented versions of Table 1 and a discussion of attrition bias in the analysis.

in more applied fields including engineering, architecture, and the hard sciences.

Table 1: Descriptive Statistics for Non-Interns and Interns

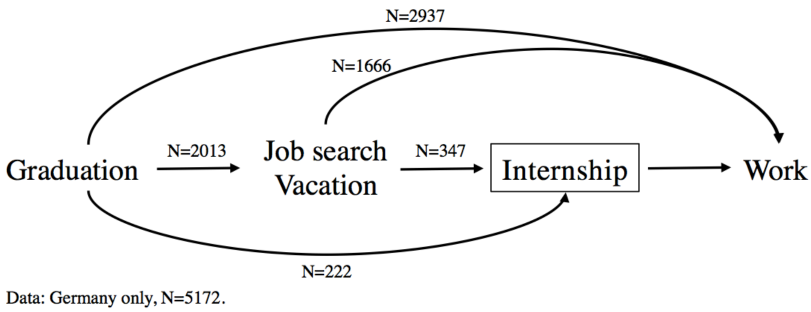
	Germany				Italy			
	Non-Interns		Interns		Non-Interns		Interns	
Variable	Mean	std. dev	Mean	std.dev	Mean	std. dev	Mean	std.dev
Age	26.96	(3.55)	27.02	(3.13)	27.062	(5.01)	26.437	(3.55)
Female	0.58	(0.49)	0.68	(0.47)	0.60	(0.49)	0.65	(0.48)
Grades	1.85	(0.55)	1.83	(0.54)	103.139	(7.98)	103.873	(7.54)
Study Duration	5.166	(1.508)	5.512	(1.448)	6.619	(3.48)	6.555	(2.67)
	Study Fields							
Psychology	0.019	(0.14)	0.054	(0.23)	0.022	(0.15)	0.163	(0.37)
Culture	0.057	(0.23)	0.11	(0.31)	n/d		n/d	
Art	0.030	(0.17)	0.044	(0.20)	n/d		n/d	
Social Sciences	0.087	(0.28)	0.105	(0.31)	0.123	(0.33)	0.134	(0.34)
Linguistics, Literature	0.074	(0.26)	0.088	(0.28)	0.068	(0.25)	0.044	(0.21)
Agriculture, Land Studies	0.057	(0.23)	0.050	(0.22)	0.020	(0.14)	0.024	(0.15)
Business, Economics	0.150	(0.36)	0.165	(0.37)	0.135	(0.34)	0.127	(0.33)
Law	0.028	(0.17)	0.022	(0.15)	0.115	(0.32)	0.032	(0.18)
Hard Sciences	0.034	(0.18)	0.021	(0.14)	0.032	(0.18)	0.020	(0.14)
Pedagogics	0.047	(0.21)	0.039	(0.19)	0.073	(0.26)	0.025	(0.16)
Engineering	0.22	(0.41)	0.123	(0.33)	0.131	(0.34)	0.095	(0.29)
Sport	0.006	(0.08)	0.001	(0.04)	0.007	(0.08)	0.003	(0.06)
Human Medicine	0.073	(0.26)	0.059	(0.24)	0.039	(0.20)	0.151	(0.36)
Geo- and Biology	0.050	(0.22)	0.066	(0.25)	0.042	(0.20)	0.035	(0.18)
Chemistry and Pharmacy	0.037	(0.19)	0.008	(0.09)	0.025	(0.15)	0.049	(0.22)
Architecture	0.032	(0.18)	0.052	(0.22)	0.042	(0.20)	0.034	(0.18)
Job search (in months)	2.254	(2.41)	4.337	(3.59)	7.598	(20.81)	7.272	(18.37)
Employment 1 year after grad.	0.512	(0.500)	0.553	(0.497)	0.512	(0.500)	0.553	(0.497)
Employment 3 years after grad.					0.684	(0.465)	0.735	(0.441)
Employment 5 years after grad.	0.684	(0.465)	0.735	(0.441)	0.782	(0.413)	0.811	(0.392)
Log-Earnings 1 year after grad.	6.775	(0.563)	6.764	(0.537)	6.775	(0.563)	6.764	(0.537)
Log-Earnings 3 years after grad.					6.945	(0.493)	6.949	(0.480)
Log-Earnings 5 years after grad.	6.945	(0.493)	6.949	(0.480)	7.086	(0.493)	7.045	(0.489)
Number of graduates	5730		726		20751		5593	

Note: Job search is mean time until first job was found, potentially including months of search inactivity in Germany and net-time of search, excluding months of search inactivity, in Italy.

For the remaining analyses, I will sustain the assumption that all graduates could in principle find paid work after graduation without detouring via an internship. This assumption is supported by mean months of job search. It is not the case that interns linger significantly longer in job search than non-interns. Rather, individuals appear to partially substitute months of job search with the internship. To illustrate this point, consider Figure 1 to see the most common paths towards regular employment. Individuals could go straight to work after graduation or could search for a while before finding an employment. About 57% of the German graduates in the sample start working within the first month after graduation, 32% find employment after a few months of search. Alternatively, graduates may take the same paths via an internship. 4% in Germany start an internship right after graduation, 7% after a few months of job/internship search.[8]

Conditional on searching for a job, German non-interns search on average for 4.43 ($\sigma = 2.90$) months. German interns start working after 4.34 ($\sigma = 3.58$) on average. This figure includes the duration of the internship, so it seems that most interns transition from the internship directly into regular employment. In Italy, the job search takes significantly longer than in Germany and non-inters spend on average 7.598 (σ=20.81) months in job search, interns 7.272 (σ =18.37) months.

Figure 1: Illustration of Common Paths of Transition



The German panel allows some further inspection into the descriptive characteristics of internships.[9] Internships are supposed to be a means of transition into the labour market. This is in line with the fact that they are more or less taken up immediately after the end of studies. The mean effective internship start date is 3.67 (σ= 3.08) months after graduation. Table 2 shows the number of internships, and their mean durations for the German data. The table confirms that internships have indeed a short-term character, lasting on average 3-4 months. There is no evidence for long-

[8]The Italian data does not allow such a fine-grained analysis.

[9]Again, unfortunately, the Italian data does not contain further information on internships, and one may only speculate on similar characteristics between both countries.

lasting *floundering* in repeated internships. The majority does only one internship before starting to work in a direct-hire job.

Table 2: Number of internships and their durations (Germany)

	Mean duration (Std. Dev.)	N
Internship 1	4.07 (3.02)	726
Internship 2	3.76 (3.15)	110
Internship 3	3.70 (2.72)	33
Internship 4	5.00 (2.45)	7
Internship 5	7.5 (0.71)	2

Finally, Table 3 displays the major reasons for why (German) graduates choose to do an internship. The table reveals that most graduates value internships as a good way to accumulate work experience and specialization. They hope the internship to serve them as a stepping stone towards a desired position afterwards. More than 50% believe in facilitating their consecutive job search. Some were even promised a regular job following the internship - however, only very few claim to have actually received a job offer following the internship. Only a small fraction of graduates opt for an internship because they have not yet found another job. This motive has to be treated with caution. It is impossible to make a qualified statement about selection effects already. The early start dates and short durations of internships suggest that they are merely used to fill a gap of transition. Nevertheless, some interns may have been unable to find a direct-hire job, which lowered their personal job requirements, and made the internship an acceptable alternative. Possibly an even larger fraction of interns has trouble finding a job, but do not confess in the survey. Overall, the picture emerges that internship participation among German graduates is voluntary, and that graduates see it as an investment into their future career from which they expect positive returns.

Table 3: Motivation to do an internship (Germany)

	Mean	Std.Dev
Acquire work experience	0.7678	0.4226
Facilitate job search through internship	0.5373	0.4990
Felt need for specialization	0.3951	0.4893
No other job found	0.3865	0.4874
Was promised a job after internship	0.2790	0.4489
Others	0.1976	0.3985

4 Conceptual Background

No research has yet analysed the labour market effects of post-graduation internships. Nevertheless, one may draw parallels to other strands of literature to anticipate their potential effects.

Several models would predict positive effects of internships on subsequent employment and earnings. First of all, internships may be seen as work experience and on-the-job training (see for example Mincer (1962); Barron et al. (1989); Keane and Wolpin (1997)), which could positively affect wage trajectories through human capital accumulation. According to job mobility models (Burdett, 1978; Jovanovic, 1979) workers switch between jobs to move to employers who are better matches for their skills, and thus pay higher wages. The empirical evidence for this job-shopping hypothesis goes back to Topel and Ward (1992). They show for the case of young American men that between-job wage growth is responsible for one-third of total wage growth of the first ten years in the labour market. Next, according to the stepping-stone literature internships could substitute spells of unemployment, and hence avoid underutilization and depreciation of human capital (Autor and Houseman, 2010; Booth et al., 2002;

de Graaf-Zijl et al., 2011; Van den Berg et al., 2002). From an employer's perspective, internships are an inexpensive way to reduce information asymmetries by learning the worker's type (Stigler, 1962). Because internships are not severely regulated through employment protection laws, employers may test-hire graduates to learn about their true ability, and devise job offers accordingly. In addition, employers may save on social benefits for the duration of the internship until a proper work contract is signed. Internships could thus increase employment, especially in markets where employment protection laws are responsible for frictions in the hiring process (Acemoglu and Angrist, 2001; Dolado et al., 2002).

On the other hand, internships could also send negative signals to employers, and inhibit hiring of interns due to adverse selection (Akerlof, 1970; Greenwald, 1986). Negative signals of interns being the low-quality selection of all graduates could originate for example if employers perceive that interns were unable to find direct-hire jobs right after graduation. Internships could also generate locking-in effects (Van Ours, 2004), as well as decrease individuals' search intensities during the internship. These factors would lower the probability of finding a high quality job to proceed to. All of the above negative signals to employers can lead to low wage offers which interns might readily accept if they are not aware of their true value for the employer (Gibbons et al., 2005), as well as when they are liquidity constraint, and thus obliged to quickly start working (Chetty, 2008). Moreover, Cockx and Picchio (2013) find that an initial employer-employee mismatch may lead to persistent scarring effects of young workers. This would especially apply if internship experiences lead to difficulties in subsequent job search, causing prolonged spells of early unemployment.

4.1 The Higher Education System and Labour Market Situation in Germany and Italy

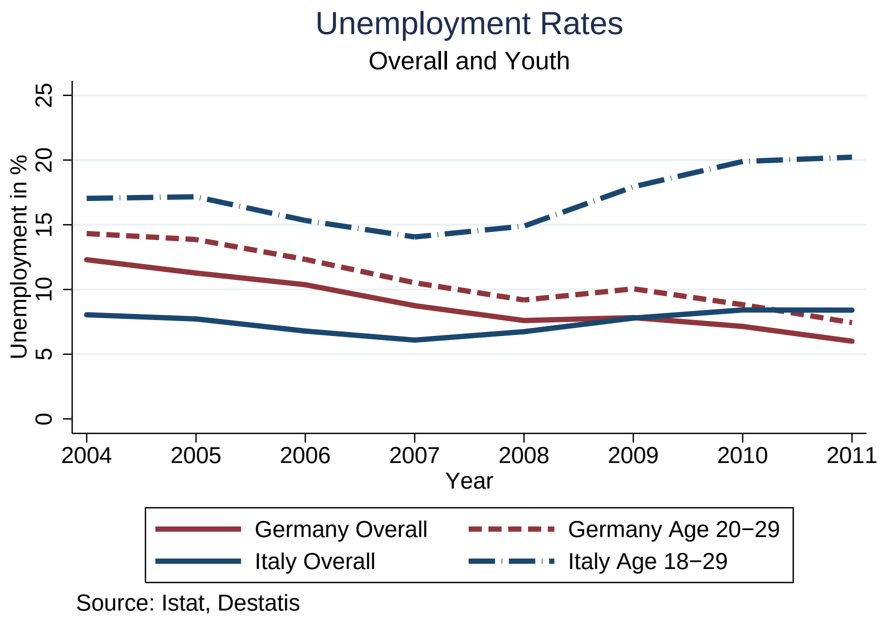
Before the Bologna Process reforms in 1999, most European countries offered 4-5 year one-cycle curricular. Those degrees were supposed to directly qualify graduates for the labour market, or to pursue Doctoral studies. Since the reform, the one-cycle degrees are re-modulated as two-cycle curricular leading first to a Bachelor's degree (usually 3-4 year curricular), and later to a Master's degree (additional 1-2 year curricular). The objective of the introduction of the shorter Bachelor curricular was to increase the speed with which young academics enter the labour market. However, most students proceed subsequently to a Master's degree. The speed of implementation of the reform differs greatly within and across countries. While in the German data from 2004/05 only about 10% of all graduates hold a Bachelor's degree, in the Italian data of the same year Bachelor graduates account for two-thirds of the full sample. Italy is indeed one of the early-adopters of the reform. Despite these differences in degree types, all graduates should be sufficiently trained to enter the job market directly.

Looking at the general labour market situation in the two countries during the observation period it becomes evident that unemployment rates are indeed higher for young workers compared to the whole working age population. Overall unemployment rates are initially higher in Germany than in Italy but there is a continuous downward trend over the observation period.[10] While the German youth unemployment rate evolves in parallel to the overall unemployment rate with a gap of only about two percentage points, one notices a much more pronounced gap in Italy. Italian youth unemployment lies between 15-20%, and thus roughly ten percentage points above the overall rate. Relating these statistics to university graduates, it is likely that

[10] It is important to point out that between 2003 - 2005 Germany implemented far-reaching labour market reforms. The so called *Hartz-Reforms* triggered, among other effects, a re-labelling of many previously inactive individuals as unemployed. Due to this fact, unemployment rates in Germany are particularly high during the years of 2004/05, and then continuously decrease over time.

these numbers are upward biased through higher unemployment among low-educated workers in the same age group. Still, they give an accurate approximation for university graduates.

Figure 2: Unemployment rates of youth and overall population (2004 - 2011)



5 Estimation Strategy and Results

5.1 OLS Estimation of Employment Status

In a first step, I estimate linear probability models and ordinary least squares regressions to show the effects of an internship experience on employment. I regress an indicator dummy for employment status at different points in time separately for Germany and Italy.[11] Linear regressions give a good benchmark estimation as a starting point. However, they do not control for any sample selection, and assume linearity in

[11]For both countries, I measure employment through the question *"Are you currently employed?"*. The results are robust to other proxies such as using earnings indicators above a certain threshold (800 or 1000 Euro).

effects. Estimates are thus likely to be biased.[12]

Table 4 displays estimations of employment status during the first wave, hence approximately one year after graduation. Panel A shows the estimations for Germany, Panel B for Italy. Column 1 regresses employment status on an internship dummy, gender, an interaction for female internship participation, and general demographic characteristics such as age, marital status, employment status of spouse, and educational attainment, as well as work status of parents. Column 2 adds controls to the first estimation related to the completed university curriculum. These include the study degree (e.g. one-cycle or Bachelor/Master degree) and study field. Column 3 additionally controls for cognitive ability through high school and university grades, and study duration. The fourth model further controls for various extra-curricular activities and qualifications. Among these are whether or not someone had a student job or other previous work experience, studied abroad, or done an internship during the studies (e.g. voluntary summer internships or mandatory internships as part of the curriculum). The last set of controls, related to job search activities, is added in column 5. These controls include when the individual has roughly started searching for employment, how many applications he or she sent, as well as whether the individual has undertaken any actions to enhance his or her chances on the job market (e.g. quick study, language courses, career centre training).

The internship dummy is significant and negative across all models for Germany, whereas it is significant but positive for Italy. It seems that the most important group of controls is added through university degrees in column 2. After including this set of variables the internship's effect increases in the German panel, and stays roughly constant throughout the other specifications. Also the R^2 jumps up at its inclusion, in both countries. Interestingly, adding controls for cognitive ability and extracurricular activities, in columns 3 and 4, does not have large effects on the estimates nor on

[12]Subsection 5.2 will adress these issues through propensity score matching.

Table 4: Linear Probability Model using OLS of Employment Status after one year

Dependent Variable: Employment Status during first wave					
	(1)	(2)	(3)	(4)	(5)
Panel A: Germany					
Internship	–0.047*	–0.059**	–0.055**	–0.056**	–0.058**
	(0.025)	(0.025)	(0.025)	(0.024)	(0.023)
Female	–0.001	0.006	0.005	–0.001	0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Female × Internship	0.010	–0.003	–0.007	–0.016	–0.022
	(0.031)	(0.031)	(0.031)	(0.030)	(0.029)
Constant	–5301.078***	–1192.385*	–1553.805**	–787.153	–334.882
	(648.528)	(640.456)	(649.977)	(679.184)	(663.201)
R^2	0.048	0.170	0.174	0.210	0.284
N	6443	6443	6443	6414	6414
Panel B: Italy					
Internship	0.071***	0.062***	0.065***	0.072***	0.022**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.009)
Female	–0.032***	–0.025***	–0.019**	–0.009	–0.018***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Female × Internship	–0.038**	–0.015	–0.013	–0.011	–0.003
	(0.015)	(0.015)	(0.015)	(0.014)	(0.011)
Constant	0.074	0.013	0.658***	1.009***	1.212***
	(0.078)	(0.099)	(0.121)	(0.230)	(0.203)
R^2	0.085	0.133	0.138	0.244	0.558
N	26344	26344	26344	26344	26344
Demographic controls	Yes	Yes	Yes	Yes	Yes
Degree controls	No	Yes	Yes	Yes	Yes
Cognitive controls	No	No	Yes	Yes	Yes
Extracurricular controls	No	No	No	Yes	Yes
Job search controls	No	No	No	No	Yes

the R^2 in either country. The study degree and field of specialization seem to be more important determinants for finding paid work at job entry, whereas academic performance is less relevant. This is line with the results from a structural model of graduates' labour market transitions and empirical evidence from the Netherlands by van der Klaauw and van Vuuren (2010). In the least parsimonious specification in column 5 one gets a hint for what may be the true difference in employment for interns compared to non-interns. The effect here is estimated to be roughly -6% in Germany. In Italy this effect amounts to an increased likelihood of being in paid work within one year after graduation of 2.2% for men, and a null effect for women.

Looking at differences in employment between interns and non-interns over time, it seems that the positive effect for Italian men is lasting and becomes even stronger over the first three years, but mostly vanishes after five years. German interns fully catch up to the non-interns within five years after graduation.[13] In both samples, women are significantly less often employed five years after graduation, but this effect is independent of the internship experience.

To conclude this preliminary set of results, internships seem to have detrimental effects on employment in Germany, but marginally positive effects in Italy. Yet, as mentioned previously, these results are likely to be biased.[14] Linear regression assumes uniform effect sizes for all observations. However, heterogeneity in effect sizes seems more plausible. For this reason the following section relaxes the linearity assumption.

5.2 Propensity Score Matching - Methodology

In this section, I introduce propensity score matching based on Rosenbaum and Rubin (1983). Matching estimators rely on the same exogeneity assumptions as linear regression, but can capture effect heterogeneity as well as non-linearity. Matching estimators are commonly used in observational data analysis. An exogenous variation in treat-

[13]There is no data available at three years after graduation for Germany.
[14]Please refer to Appendix A3 for robustness tests using logistic regressions of employment status.

Table 5: Linear Probability Models for Employment over time

Dependent Variable: Employment Status			
	12 mo after grad	3 yrs after grad	5 yrs after grad
Panel A: Germany			
Internship	–0.058**		–0.004
	(0.022)		(0.018)
Female	–0.012		–0.119***
	(0.009)		(0.011)
Female × Internship	–0.022		0.022
	(0.029)		(0.025)
Constant	–334.882		361.818
	(663.201)		(845.758)
R^2	0.284		0.074
N	6414		6412
Panel B: Italy			
Internship	0.022**	0.044**	0.015*
	(0.009)	(0.009)	(0.009)
Female	–0.018***	–0.024***	–0.034***
	(0.005)	(0.007)	(0.006)
Female × Internship	–0.003	0.004	0.009
	(0.011)	(0.012)	(0.012)
Constant	1.212***	0.431*	0.372
	(0.203)	(0.222)	(0.269)
R^2	0.558	0.243	0.139
N	26344	26344	26344
Demographic controls	Yes	Yes	Yes
Degree controls	Yes	Yes	Yes
Cognitive controls	Yes	Yes	Yes
Extracurricular controls	Yes	Yes	Yes
Job search controls	Yes	Yes	Yes

ment assignment that leads to clearly identifyable treatment effects is often absent. Awareness about selection into the treatment is required and one needs to handle the data accordingly.

The basic idea behind matching estimators is to find “statistical twins” where one is part of the treatment and the other of the control group. Such individuals are then matched, and the treatment effect is estimated by averaging outcome differences across these matched pairs. Individuals do not need to be matched uniquely in pairs. Depending on the matching strategy several control individuals are matched to the same treated individual.

A group of matching estimators, as the one I apply to my analysis, use the propensity score. The propensity score describes the probability of an individual to be in the treatment group, given its observable characteristics. Matching estimators rely on the assumption that only observable characteristics determine selection into the treatment. This assumption is known as *selection on observables* or *unconfoundness*, meaning that all relevant characteristics for determining treatment participation and outcomes are observed. If this assumption holds true, then, conditional on observables, selection into the treatment is as good as random. Statements about counterfactual outcomes necessitate this assumtion.

The following condition expresses unconfoundness, where Y_{0i} describe outcomes of individuals in the control group and Y_{1i} those in the treatment group. X_i represents the vector of observables, T_i indicates treatment status:

$$(Y_{0i}, Y_{1i}) \perp T_i | X_i$$

The propensity score theorem by Rosenbaum and Rubin (1983) then states that

$$(Y_{0i}, Y_{1i}) \perp T_i | p(X_i) \qquad \text{with} \qquad 0 < Pr(T_i = 1 | X_i) < 1$$

The propensity score summarizes all information from observable characteristics in one metric. The propensity score describes the likelihood of an individual with observable characteristics X_i to be treated. It therefore lies between 0 and 1. The second condition of the theorem is known as the *overlap condition.* It states that for any vector of observable characteristics, there need to be treated and untreated individuals in the sample. Specific characteristics must not lead to sure treatment or control group assignment. Otherwise, selection would be easily identifiable and not random. Given the propensity score theorem, matching on the propensity score is equivalent to matching on observables directly.

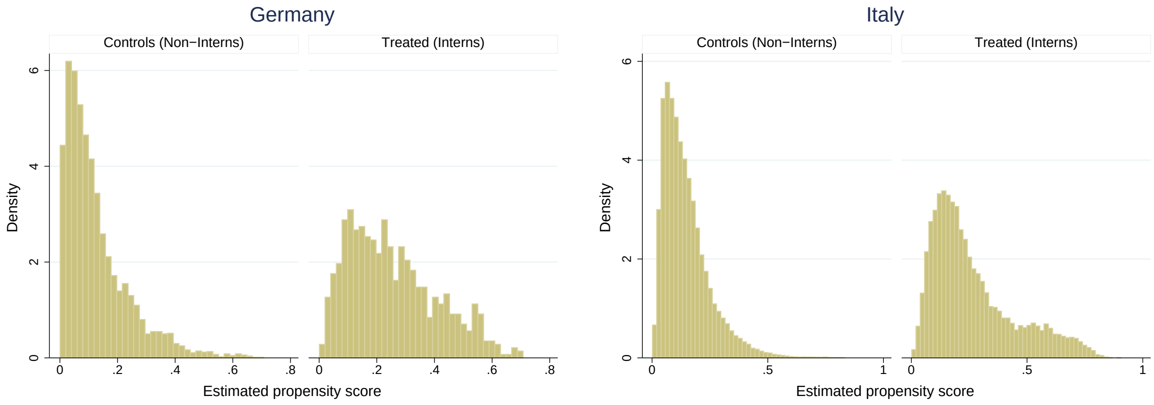
To apply propensity score matching, the first step consists in estimating the propensity score. It is common to estimate a logit model of the binary treatment variable.[15] I run a logistic regression on the internship dummy with several controls. More precisely, I use the same controls as in the least parsimonious OLS specifications to maintain comparability of the different estimation methods.

$$internship_i = \beta_0 + \beta_1 Demogr_i + \beta_2 Degree_i + \beta_3 Cogn_i + \beta_4 Ext.curr_i + \beta_5 Search_i + \varepsilon_i$$

To obtain an unbiased propensity score, all relevant characteristics that impact treatment assignment as well as outcomes need to be included in its estimation. Next the overlap condition needs to be verified, although there exist no formal tests of the unbiasedness of the propensity score, nor of the overlap condition. The lack of such a test is due to the dependence on unobservable characteristics of both the propensity score and the overlap condition, just as the unconfoundness assumtion which also cannot be tested. Figure 3 supports the validity of my propensity score approach. Visibly my data contains control and treated individuals for any combination of observables.

[15] See the seminal application of propensity score matching from Dehejia and Wahba (1999).

Figure 3: Overlap of the Propensity Scores



The next step identifies matching pairs, or matching groups, of similar individuals based on the propensity score. Different methods establish what *similar* means. All of them rely on distance measures between treated and control individuals using the propensity score. I apply so called radius, or caliper, matching. Each treated individual is matched to all controls that lie within a certain radius. Caliper matching has the advantage of allowing only "good" matches in the sense that only very similar individuals are matched.[16] This comes at the cost of some observations remaining unmatched if no such similar control individual exists.[17] I use matching with replacement such that the same control individual may be matched to more than one treated. Matching with replacement may increase the number of matches. However, my results do not vary due to this condition, because of the large number of control individuals compared to the number of treated.

[16]Given the extensive overlap, I am able to use a rather tight caliper of 0.05 without leaving many observations unmatched. This caliper ensures a high quality of the matches. Results remain qualitatively unchanged for larger and even tighter calipers, the data may be obtained on request.

[17]This is opposed to nearest neighbor matching where every treated individual will be matched to the individual(s) that is (are) the most similar. Here, every single treated individual will be matched. However, some matches may be of poor quality if the individual is not in fact close to its match in its observable characteristics. See Rosenbaum and Rubin (1985) for an overview of matching methods based on the propsensity score.

5.3 Propensity Score Matching for Employment

Table 6 displays the results for all employment outcomes in parallel for both countries. The matched samples contain 6,377 individuals for Germany and 26,332 for Italy.[18] The first row of each estimation shows unconditional means of employment for treated and control individuals (i.e. for interns and non-interns), their difference, standard errors and a T-test of significance. The second row shows the same measures for the matched sample. The first column of the second row displays the unconditional mean employment of interns who lie on common support. The Controls column gives the estimated counterfactual outcome based on the matched controls. The difference of means depicts the average treatment effect on the treated (ATT). The ATT describes the estimated difference in employment for non-interns, had they done an internship. The results confirm the descriptive statistics of Italian youth unemployment exceeding the German during my observation period. The German average employment rate one year after graduation is already high at around 84-87%, whereas employment is much lower in Italy, around 51-55%. While employment then stagnates in Germany, it gradually increases to over 80% over the next three to five years in Italy.

Table 6: Results from Propensity Score Matching, Employment

	Panel A: Germany					**Panel B:** Italy				
Sample	Treated	Controls	Difference	S.E.	T-Stat	Treated	Controls	Difference	S.E.	T-Stat
	Employment Status approx. 1 year after graduation									
Unmatched	0.836	0.869	-0.033	0.014	-2.42	0.553	0.512	0.041	0.008	5.41
ATT	0.834	0.908	-0.074	0.015	-4.82	0.553	0.579	-0.026	0.010	-2.66
	Employment Status approx. 3 years after graduation									
Unmatched						0.735	0.684	0.051	0.007	7.34
ATT						0.735	0.728	0.008	0.009	0.87
	Employment Status approx. 5 years after graduation									
Unmatched	0.852	0.861	-0.010	0.014	-0.71	0.811	0.782	0.029	0.006	4.73
ATT	0.852	0.847	0.005	0.015	0.23	0.811	0.811	-0.001	0.008	-0.07

In the German sample, Panel A, the ATT amounts to significant -7.4% during the

[18] 283 German control individuals and 10 treated as well as 15 Italian treated individuals are off support and remain unmatched.

first wave and becomes insignificant five years after graduation (0.5%). The matching thus confirms the immediate but short-lived negative effect of an internship on subsequent employment, although the estimated effect in the matching analysis is slightly larger than in the previous OLS estimation. In the Italian sample, Panel B, contrary to the OLS estimation, the ATT for employment during the first wave is now negative as well. It amounts to significant -2.6%. The ATT in the two remaining waves, three and five years after graduation, are virtually zero and insignificant. Therefore, the matching estimation in the Italian sample also points towards an initial negative effect of internships on employment. But, just as in Germany, this negative effect is not lasting and already within three years, interns catch-up to their non-intern peers.

5.4 Results for Monthly Earnings

Having established the effects of internships on employment, I now look at differences in monthly earnings. In the earnings dimension, the German data offers an additional observation. German graduates report not only their current earnings during the first wave, i.e. approx. 1 year after graduation, but also the monthly earnings of their first job. This measure for starting earnings excludes earnings during an internship.

Table 7 displays the results for all earnings outcomes, again in parallel for both countries. The matched samples contain 4,066 individuals for Germany and 10,665 for Italy.[19] In the German sample, Panel A, the ATT measures an earnings gap of significant -21% at job start. This gap decreases quickly with the first months of experience, but still amounts to a significant -12.3% one year after graduation. The earnings results thus consolidate the negative effects of internships indicated already for employment. Analogous to the employment results, there is convergence in earnings within five years. The German ATT after five years is only -2.6%, and becomes insignificant.

[19] 156 German control individuals and 4 treated as well as 4 Italian treated individuals are off support and remain unmatched. Sample sizes have especially fallen because of the use of log-earnings, dropping all individuals reporting zero earnings.

Table 7: Results from Propensity Score Matching, Earnings

	Panel A: Germany					**Panel B:** Italy				
Sample	Treated	Controls	Difference	S.E.	T-Stat	Treated	Controls	Difference	S.E.	T-Stat
	Monthly Starting Earnings									
Unmatched	6.988	7.295	-0.306	0.040	-7.58					
ATT	6.992	7.202	-0.210	0.045	-4.71					
	Earnings approx. 1 year after graduation									
Unmatched	7.251	7.431	-0.180	0.036	-5.01	6.806	6.862	-0.056	0.012	-4.86
ATT	7.250	7.373	-0.123	0.041	-3.02	6.81	6.834	-0.027	0.013	-2.02
						Earnings approx. 3 years after graduation				
Unmatched						7.043	7.060	-0.017	0.009	-1.82
ATT						7.043	7.056	-0.012	0.011	-1.15
	Earnings approx. 5 years after graduation									
Unmatched	7.980	8.079	-0.099	0.024	-4.04	7.148	7.157	-0.010	0.009	-1.02
ATT	7.979	8.006	-0.026	0.025	-1.05	7.149	7.163	-0.015	0.011	-1.33

In the Italian sample, Panel B, similar to the matching results for employment, the ATT for earnings one year after graduation is small, but significantly negative as well, -2.7%. The ATT in the two remaining waves, three and five years after graduation, are even smaller and lose significance again. Therefore, the matching estimation in the Italian sample also points towards an initial loss in monthly earnings.[20]

5.5 Results for Work and Life Satisfaction

In the preferred matching analyses, the effects of post-graduate internships on earnings and employment are negative in both observed countries. However, the descriptive statistics suggest that graduates opt voluntarily into internships because they actually expect positive returns from them. The next step of my analysis is therefore to look at the effects of internships on work and life satisfaction. Possibly, graduates choose to do an internship because they expect to find a job that suits them better in other dimensions than pay. To this end, I look at various satisfaction measures, which are reported in the graduate panels. The German satisfaction scales go from 1 to 5 where

[20] OLS gives qualitatively similar results with large negative effects for Germany, and null effects for Italy. See Table A4 in the appendix for the corresponding regressions.

higher values imply larger satisfaction levels. For Italy the scales go from 1 to 10, also in ascending order. I again match individuals based on the propensity score to subsequently measure differences in satisfaction levels for each measure. Tables 8 and 9 report the ATT and T-test for each measure.[21]

Table 8: Results from Propensity Score Matching for different work satisfaction measures during first wave, Germany

Dep. Var.	Internship	T-Stat
Job Security	-0.175	-2.02
Earnings	-0.260	-2.93
Career Perspectives	-0.432	-5.04
Skill Match	-0.404	-5.37
Work-Life-Balance	-0.235	-2.90
Working Atmosphere	-0.283	-4.60
Job Contents	-0.343	-5.32
Current Position	-0.284	-3.65
Work Conditions	-0.293	-4.10
Training Possibilities	-0.371	-4.46

Note: The above table only reports the ATT and respective T-statistics from the Propensity Score Matching analyses for Interns in comparison to Non-Interns. The full version of the table may be found in the Appendix A5.

Evidently, interns are not more satisfied with their jobs than non-interns. All differences in satisfaction levels are negative and significant for Germany. For Italy, most differences remain insignificant but are still mostly negative as well. Strikingly in both countries, interns seem to be unsatisfied with their job security. Moreover, Italian interns are significantly less satisfied with the flexibility of their working hours.

5.5.1 Regression vs. Propensity Score Matching

As seen in the previous sections, linear regression and propensity score matching provide similar results but sometimes differ in magnitude and qualitative directions. These

[21] The full matching tables are displayed in Tables A5 and A6 in the Appendix. In the same appendix may be also found ordered logistic regressions in Table A7. Ordered logistic regressions take the logic ordering of ordinal scales into account without assuming continuity in the dependent variables and are thus a useful robustness check to verify the matching analyses.

Table 9: Results from Propensity Score Matching for different work satisfaction measures during first wave, Italy

Dep. Var.	Internship	t-stat
Job Security	-0.213	-1.93
Earnings	-0.052	-0.23
Career Perspectives	-0.279	-1.13
Skill Match	-0.143	-1.51
Flexible Working Hours	-0.270	-2.53
Leisure Time	-0.004	-0.03
Work Place	0.050	0.29
Colleagues	-0.149	-0.33
Prestige of Work	-0.109	-0.83
Social Impact	-0.095	-0.66
Independence / Autonomy	-0.064	-0.70
Overall Work Sat.	-0.090	-0.91

Note: The above table only reports the ATT and respective T-statistics from the Propensity Score Matching analyses for Interns in comparison to Non-Interns. The full version of the table may be found in the Appendix A6. The satisfaction analyses for Italian graduates are based on pre-Bologna one-cycle curricular graduates, no data is available for two-cycle (ie. Bachelor) graduates.

similarities do not surprise since both methods rely on the same exogeneity assumptions. Estimates differ due to the underlying weighting of estimates.[22] Linear regression uses variance-based weights whereas matching uses weights based on the propensity score. OLS give more weights to observations for which there is an equal number of treated and controls. This is where the conditional variance in treatment participation is the largest. The matching estimator gives more weight to observations with the most treated individuals. Take a look back at the overlap graph in Figure 3 to see that the distributions of treated and controls resemble each other more in the Italian data. The German graph shows relatively more dispersion on the side of the interns, in comparison to the distribution of controls. Such differences indicate that effect heterogeneity is more important in Germany compared to Italy. In the Italian data, the results from OLS and matching are indeed very similar. Internships robustly do not trigger large effects on subsequent employment or earnings. For the German sample

[22]See Angrist (1998) and Angrist and Krueger (1999) for more details and derivations.

on the contrary, the matching estimator delivers more reasonable results, especially for earnings, while OLS seems to overestimate the negative effect of internships.[23]

6 Discussion

The preceding results have shown negative, though short-lived, effects of internships on initial labour market performance. The effects are more pronounced in Germany than in Italy. Employment and earnings trajectories of interns in both countries are characterized by a catching-up to their non-intern peers within a few years. Despite these rather discouraging effects, individuals seem to voluntarily opt into internships. Graduates could in principal find direct-hire jobs with their degrees alone. But since they expect positive returns, they readily accumulate these experiences.[24] It is therefore quite puzzling to find negative returns to internships while they are being viewed as something useful by the graduates themselves.

There are different reasons why internships could trigger adverse effects at job entry without having lasting effects. To begin with, recall that there are no observable differences in key characteristics between interns and non-interns. In addition, internships last only a few months, so they do not cause important differences in the accumulation of work experience in comparison to non-interns. Nevertheless, interns receive lower initial wage offers. It seems plausible that asymmetric information, negative signalling and search behaviour are important ingredients to the findings. More precisely, two mechanisms might be simultaneously at play. First, if employers perceive interns as the negative selection of all graduates, and second, if interns are themselves unsure about their type, low wage offers could lead to an initial, though short-lived, equilibrium match (Greenwald, 1986; Kahn and Lange, 2014). Search behaviour (Sattinger, 1995) and liquidity constraints (Chetty, 2008) may further encourage such suboptimal

[23]See Table A4 for OLS regressions of monthly earnings over the panel waves.

[24]This was suggested by the German survey questions on the motivation to do an internship in Table 3.

contracts. With the acquisition of experience and tenure, as suggested for example by Gibbons et al. (2005), workers and employers learn about unobserved skills and move to higher wage matches. Indeed, favorable evidence can be found in the German panel that many individuals switch employers, and even industries, between the internship and first job, and display job mobility also thereafter.[25] By trend, those who stay employed within the same industry seem to perform better than those who switch industries between the internship and first direct-hire job. Job switching behaviour has been found to have positive effects on wage growth by Topel and Ward (1992) as well as for example by Oreopoulos et al. (2012); Del Bono and Vuri (2011); von Wachter and Bender (2006). Von Wachter and Bender 2006 as well as Oreopoulos et al. (2012) suggest that wage growth through job-shopping is particularly steep for higher skilled workers. Additionally, a recent study by Gius (2014) showed that job changes within occupation or within industry can increase wages, whereas changes across industry and occupation can be detrimental to earnings.

My results clearly speak against scarring effects through internships (see Cockx and Picchio (2013) for a recent review). Internships last merely a few months, and signs indicating floundering in numerous internships, which could cause long-term harm to human capital accumulation, are absent. Furthermore, the initial gap in earnings is temporary, and there are no measurable *scars* remaining three to five years after graduation.

The effects of internships differ in magnitude between Germany and Italy. It is tempting to relate this disparity to differences in institutional factors and general labour market conditions in the observed countries. Italy is characterized by much higher youth unemployment rates in comparison to Germany. The German labour market generally seems to quickly absorb new graduates (Ryan, 2001; von Wachter and Bender, 2006) while transitions in Southern Europe go less smoothly (Ryan, 2001; García-Pérez

[25]See Table A8 in the Appendix for descriptive statistics of the industries of internships and first jobs.

and Muñoz-Bullón, 2011; Dolado et al., 2002). Because graduates could rather easily find direct-hire jobs right after graduation in Germany, the above described negative signalling effects of internships might be stronger in the German labour market. In Italy positive effects due to screening of workers might offset negative signalling. If employers can test workers and save initially on social security payments before deciding to hire them, internships might be a regular path into employment (Dolado et al., 2002). Also, the negative effects of internships in Italy are less robust than the German results. It is not unlikely that net effects for some Italian interns are even positive. In line with Oreopoulos et al. (2012) who find that the most able individuals succeed to overcome initial adverse labour market conditions at job entry, it could be that the best interns in Italy can separate from the crowd of young job seekers and find decent job matches. Therefore, the highly different contexts of the labour market dynamics in both countries can, at least in part, rationalize my results.

7 Conclusion

Over the last decade, internships have gained a reputation of facilitating the entry to the labour market. A growing number of graduates do internships following their graduation in order to then find a direct-hire job. The phenomenon of the so called *Generation Internship* has gained momentum at university placement agencies as well as in the public press. However, their efffects on labour market dynamics have never been carefully analysed. Contrary to interns' expectations, I find that internships are not a very useful tool of transition. Internships can serve as a means of orientation, but depending on the labour market dynamics, employers do not value them. Therefore, short term practical work experiences should probably be conducted during higher education, for example through mandatory summer internships. This way, students may acquire the orientation they lack from theoretical studies, without receiving the negative label a post-graduate internship seems to put onto them.

As a first step, I use linear regressions with an increasing number of control variables to estimate differences in employment between interns and non-interns. According to OLS estimations, German interns are 6% less likely to be employed within the first year after graduation. In Italy, OLS estimates a small, but positive, 2.2%, effect of internships on employment. These differences are mostly constant across different models. Especially, they do not vary with the inclusion of cognitive ability controls, but the effects mainly depend on the field of study. Because the linear estimation is likely to produce biased estimates due to effect heterogeneity in the observed population, I use propensity score matching for all following analyses. Matching confirms the negative employment effects for Germany and also finds negative effects for Italy. Italian interns are 2.6% less likely to be in paid work within the first year of graduation. In both panels, there is catching up of interns to non-interns within five years after graduation. The adverse effects on employment are further underlined by poorer monthly earnings of interns. There are large and highly significant negative effects of internships on monthly earnings. Earnings penalties amount to -12 to -21% over the first year in Germany, and to -2.7% in Italy. These effects decrease with work experience and again vanish within five years after graduation.

It is puzzling to find that internships trigger adverse effects while being highly appreciated on the side of the interns. Internships are promoted as a means of facilitating the labour market entry for inexperienced young workers, and are perceived as such by the interns themselves. Internships are very popular among university graduates. They happily enrol into them because they are expecting positive returns from them, certainly not the opposite. I conjecture that the initial detrimental effects of internships are due to asymmetric information and negative signalling. Employers must believe that interns were unable to find a direct-hire job, thus believing them to be a negative selection of all interns, and hence offer them lower earnings. Graduates may readily accept such contracts if they are unaware of their actual value to the employer, as well as when they are liquidity constraint after years of studying. Depending on the general labour market conditions, the magnitude of such effects may vary in the degree to which they affect frictions in the arrival of job offers, as well as the interns' bargaining power in wage negotiations. Although interns are not measurably different from non-interns in key characteristics, and there do not seem to be relevant patterns of selection out of the panel, it remains an open question whether they are different in unobservables such as attitudinal factors that impact success during job interviews and wage negotiations. Future work may want to look more carefully at the mechanisms leading to differences in hiring decisions of interns and non-interns, for example through an experimental approach. This would at the same time tackle issues with the unconfoundness assumption that underlies my analyses.

To conclude, interns underperform non-interns particularly at the immediate labour market entry and catch up to them later. Job-shopping and learning effects, are probable causes of the convergence to non-intern performance in employment and earnings. With experience, workers and employers learn about unobservable skills of the interns, and consider these skills in subsequent wage negotiations. Indeed, a large, and lasting, negative effect would be difficult to reconcile with the fact that graduates enroll into internships voluntarily.

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8 Appendix:

8.1 Descriptive Statistics

I here display augmented versions of the descriptive statistics displayed in Section 3. Tables A1 and A2 show means of key characteristics for the selected samples of my analyses and confronts them with the same means of individuals who were dropped from the analyses due to panel drop-out. That is, I compare individuals who answered to all survey waves to those who answered only the first wave in Germany (only the first or first two waves in Italy).

In Germany, Table A1, there are no evident patterns of attrition bias. Interns and non-interns have similar key characteristics if they answered both panel waves, or only the first. They show important similarities in control dimensions, such as age, gender and university grades, as well as in the outcome dimensions earnings and employment.

Table A1: Attrition analysis using Panel Drop-Outs, Germany

	Interviewed both waves				Interviewed only first wave			
	Non-Interns		Interns		Non-Interns		Interns	
Variable	Mean	std. dev	Mean	std.dev	Mean	std. dev	Mean	std.dev
Age	26.96	(3.55)	27.02	(3.13)	26.97	(3.40)	27.10	(3.21)
Female	0.58	(0.49)	0.68	(0.47)	0.54	(0.50)	0.66	(0.47)
Grades	1.85	(0.55)	1.84	(0.54)	1.89	(0.55)	1.96	(0.53)
Study Duration	5.17	(1.51)	5.51	(1.45)	5.13	(1.55)	5.32	(1.50)
Log-Starting-Earnings	7.282	(0.81)	6.977	(0.87)	7.279	(0.79)	7.042	(0.82)
Log-Earnings 1 year after grad.	7.417	(0.71)	7.239	(0.78)	7.392	(0.72)	7.245	(0.74)
Log-Earnings 2 years after grad.	8.032	(0.509)	7.960	(0.47)				
Employment 1 year after grad.	0.869	(0.34)	0.836	(0.37)	0.844	(0.36)	0.783	(0.41)
Employment 5 years after grad.	0.861	(0.35)	0.851	(0.36)				
Job search (in months)	2.255	(2.41)	4.337	(3.59)	2.173	(2.27)	4.631	(3.76)
N	5730		730		4741		586	

In Italy, Table A2, there are a few directional differences, although none are statistically significant. Subjects that do not respond to all panel waves are by trend younger, male, have lower grades, and slightly shorter study durations. Also, interns that only answer the first questionnaire seem to be, on average, more often employed than the remaining individuals. However, note that monthly earnings do not differ between the different samples. Hence, it is not the case, in either country, that the most able individuals (interns or not) drop out of the panel, leaving a negative selection for the full analyses. Biases of attrition do not seem to mitigate the validity of the main analyses.

Table A2: Attrition analyses using Panel Drop-Outs, Italy

	Interviewed all three waves				Interviewed first 2 waves				Interviewed only first wave			
	Non-Interns		Interns		Non-Interns		Interns		Non-Interns		Interns	
Variable	Mean	std. dev	Mean	std.dev	Mean	std. dev	Mean	std.dev	Mean	std. dev	Mean	std.dev
Age	27.062	(5.012)	26.437	(3.554)	25.585	(4.639)	25.437	(3.561)	26.702	(6.549)	25.528	(4.768)
Female	0.601	(0.49)	0.654	(0.476)	0.605	(0.489)	0.662	(0.473)	0.599	(0.49)	0.625	(0.484)
Grades	103.139	(7.978)	103.873	(7.541)	102.447	(7.797)	102.422	(7.997)	102.162	(8.106)	101.569	(8.087)
Study Duration	6.619	(3.478)	6.555	(2.666)	5.053	(2.882)	5.397	(2.595)	4.346	(2.451)	4.459	(2.108)
	Outcomes											
Log-Earnings 1 year after grad.	6.775	(0.563)	6.764	(0.537)	6.701	(0.620)	6.759	(0.543)	6.841	(0.587)	6.823	(0.515)
Log-Earnings 3 years after grad.	6.945	(0.493)	6.949	(0.480)	6.907	(0.534)	6.969	(0.469)				
Employment 1 year after grad.	0.512	(0.500)	0.553	(0.497)	0.461	(0.499)	0.581	(0.497)	0.594	(0.491)	0.654	(0.476)
Employment 3 years after grad.	0.684	(0.465)	0.735	(0.441)	0.592	(0.491)	0.732	(0.443)				
Net job search (in months)	7.598	(20.814)	7.272	(18.370)	7.867	(22.110)	6.717	(17.445)	7.600	(21.968)	7.591	(19.894)
N	20,751		5,593		9,231		1,886		29,746		4,450	

8.2 Additional Results

8.2.1 Robustness of Results for Employment Status

A robustness check of the OLS analyses in Section 5.1 can be found in Table A3. I here apply logistic regressions to the estimation of employment status using otherwise the same specifications as before. The results resemble the linear probability models in Table 4.

Table A3: Logistic regression of Employment Status after one year

Dependent Variable: Employment Status during first wave	(1)	(2)	(3)	(4)	(5)
Panel A: Germany					
Internship	–0.396*	–0.601***	–0.558***	–0.653***	–0.696***
	(0.202)	(0.217)	(0.216)	(0.222)	(0.215)
Female	–0.130	0.001	–0.010	–0.036	0.174
	(0.084)	(0.098)	(0.100)	(0.104)	(0.115)
Female × Internship	0.136	0.002	–0.030	–0.129	
	(0.243)	(0.259)	(0.259)	(0.267)	
Constant	323.939***	106.553***	128.533***	81.856**	61.768
	(45.133)	(31.388)	(35.293)	(39.723)	(37.613)
N	6443	6443	6443	6401	6401
Panel B: Italy					
Internship	0.314***	0.281***	0.303***	0.364***	0.152*
	(0.055)	(0.056)	(0.056)	(0.061)	(0.080)
Female	–0.134***	–0.110***	–0.080**	–0.049	–0.164***
	(0.030)	(0.034)	(0.034)	(0.037)	(0.052)
Female × Internship	–0.162**	–0.062	–0.062	–0.051	0.038
	(0.067)	(0.068)	(0.068)	(0.074)	(0.096)
Constant	–2.040***	–2.014***	–0.052	–1.128	0.829
	(0.645)	(0.663)	(0.768)	(1.818)	(2.429)
N	26336	26336	26336	26336	17833
Demographic controls	Yes	Yes	Yes	Yes	Yes
Degree controls	No	Yes	Yes	Yes	Yes
Cognitive controls	No	No	Yes	Yes	Yes
Extracurricular controls	No	No	No	Yes	Yes
Job search controls	No	No	No	No	Yes

8.2.2 OLS on Earnings

Table A4: Linear Regressions for Germany and Italy over time

Dependent Variable: Gross monthly earnings (in logs)				
	Job start	12 mo after grad	3 yrs after grad	5 yrs after grad
Panel A: Germany				
Internship	–0.345***	–0.251***		–0.071**
	(0.064)	(0.055)		(0.031)
Female	–0.208***	–0.188***		–0.216***
	(0.024)	(0.020)		(0.014)
Female × Internship	0.191**	0.184***		0.113***
	(0.079)	(0.068)		(0.038)
Constant	–1700.097	–2004.834		–2584.547**
	(1553.575)	(1431.798)		(1219.705)
R^2	0.375	0.439		0.305
N	4719	4814		5690
Panel B: Italy				
Internship		–0.001	0.011	0.012
		(0.009)	(0.013)	(0.013)
Female		–0.151***	–0.144***	–0.188***
		(0.012)	(0.010)	(0.010)
Female × Internship		.0031	0.004	0.024
		(0.021)	(0.017)	(0.017)
Constant		7.356***	7.362***	7.243***
		(0.455)	(0.336)	(0.368)
R^2		0.249	0.248	0.245
N		10672	10672	10672
Demographic controls	Yes	Yes	Yes	Yes
Degree controls	Yes	Yes	Yes	Yes
Cognitive controls	Yes	Yes	Yes	Yes
Extracurricular controls	Yes	Yes	Yes	Yes
Job search controls	Yes	Yes	Yes	Yes

8.2.3 Work and Life Satisfaction

The following Tables A5 and A6 show the full propensity score matching analyses for the different satisfaction measures for Germany and Italy respectively.

Table A5: Results for Satisfaction from Propensity Score Matching, Germany

Sample	Treated	Controls	Difference	S.E.	T-Stat
		Job Security			
Unmatched	2.130	1.937	0.194	0.074	2.60
ATT	2.115	2.291	-0.175	0.087	-2.02
		Earnings			
Unmatched	2.307	2.268	0.039	0.078	0.50
ATT	2.301	2.561	-0.260	0.089	-2.93
		Career Perspectives			
Unmatched	2.040	2.160	-0.119	0.077	-1.55
ATT	2.030	2.461	-0.432	0.086	-5.04
		Skill Match			
Unmatched	1.691	1.782	-0.091	0.068	-1.34
ATT	1.677	2.080	-0.404	0.075	-5.37
		Work-Life-Balance			
Unmatched	1.940	2.037	-0.096	0.073	-1.32
ATT	1.926	2.160	-0.235	0.081	-2.90
		Working Atmosphere			
Unmatched	1.158	1.266	-0.107	0.055	-1.94
ATT	1.153	1.436	-0.283	0.061	-4.60
		Job Contents			
Unmatched	1.427	1.509	-0.082	0.060	-1.36
ATT	1.416	1.742	-0.325	0.067	-4.88
		Current Position			
Unmatched	1.782	1.770	0.012	0.068	0.18
ATT	1.768	2.052	-0.284	0.078	-3.65
		Working Conditions			
Unmatched	1.566	1.650	-0.084	0.064	-1.30
ATT	1.556	1.849	-0.293	0.072	-4.10
		Training Possibilities			
Unmatched	1.928	1.965	-0.038	0.074	-0.51
ATT	1.911	2.282	-0.371	0.083	-4.46

Note: N=6.377.

Table A6: Results for Satisfaction from Propensity Score Matching, Italy

Sample	Treated	Controls	Difference	S.E.	T-Stat
		Job Security			
Unmatched	6.203	6.520	-0.317	0.088	-3.59
ATT	6.206	6.419	-0.213	0.110	-1.93
		Earnings			
Unmatched	6.932	7.007	-0.075	0.182	-0.41
ATT	6.931	6.983	-0.052	0.226	-0.23
		Career Perspectives			
Unmatched	6.952	7.153	-0.200	-0.200	-1.00
ATT	6.953	7.232	-0.279	0.247	-1.13
		Skill Match			
Unmatched	6.534	6.394	0.141	0.076	1.85
ATT	6.530	6.673	-0.143	0.095	-1.51
		Flexible Working Hours			
Unmatched	6.845	7.116	-0.271	0.086	-3.14
ATT	6.847	7.117	-0.270	0.107	-2.53
		Work Place			
Unmatched	7.706	7.704	0.003	0.136	0.02
ATT	7.708	7.658	0.050	0.175	0.29
		Colleagues			
Unmatched	10.678	10.717	-0.039	0.355	-0.11
ATT	10.683	10.831	-0.149	0.446	-0.33
		Prestige of Work			
Unmatched	6.865	6.938	-0.073	0.112	-0.66
ATT	6.864	6.973	-0.109	0.132	-0.83
		Social Impact			
Unmatched	7.250	7.394	-0.144	0.113	-1.27
ATT	7.246	7.341	-0.095	0.144	-0.66
		Independence/Autonomy			
Unmatched	7.435	7.571	-0.136	0.073	-1.88
ATT	7.433	7.497	-0.064	0.091	-0.70
		Overall Work Satisfaction			
Unmatched	7.234	7.261	-0.027	0.075	-0.36
ATT	7.235	7.325	-0.090	0.099	-0.91

Note: The satisfaction analyses for Italian graduates are based on pre-Bologna one-cycle curricular graduates, no data is available for two-cycle (ie. Bachelor) graduates. N=10.105.

Table A7: Ordered logit for different work satisfaction measures, 1 year after graduation

Panel A: Germany

Dep. Var.	Internship	t-stat
Job Security	-0.242**	-2.041
Earnings	-0.432***	-3.638
Career Perspectives	-0.449***	-3.954
Skill Match	-0.523***	-4.653
Work-Life-Balance	-0.321***	-3.077
Working Atmosphere	-0.487***	-4.330
Job Contents	-0.428***	-3.806
Position	-0.400***	-3.349
Work Conditions	-0.424***	-3.890
Training Possibilities	-0.384***	-3.353
Family-Friendly-Policies	-0.351***	-3.277

Panel B: Italy

Dep. Var.	Internship	t-stat
Job Security	-0.120**	-2.149
Earnings	-0.037	-0.640
Career Perspectives	0.010	0.180
Skill Match	0.096*	1.769
Flexible Working Hours	-0.162***	-2.647
Leisure Time	-0.182***	-3.113
Work Place	-0.004	-0.071
Colleagues	-0.061	-1.055
Prestige of Work	0.129**	2.252
Social Impact	-0.090	-1.605
Independence/Autonomy	-0.131**	-2.182
Overall Work Sat.	-0.012	-0.221

Table A7 complements the analyses using ordered logistic regressions. I regress the different work and life satisfaction measures using basic demographics and degree controls. For brevity, I only report the internship coefficient and abstract from the rest. The full estimation can be obtained on request. All satisfaction measures show up significant in Germany, a few less in Italy in the ordered logistic regressions. However, the overall impression remains that internships negatively affect work and life satisfaction. At best, they remain effectless, but they clearly never turn positive.

8.3 Discussion

Table A8 shows descriptive statistics suggesting that internships are done in different industries than those in which individuals start working under regular employment. This data is unfortunately only available in the German panel. Internships in Germany are for example often done in low-wage industries such as media and publishing as well as in the arts and culture. For a first employment on the other hand there is only a negligible number of jobs in these industries. As a matter of fact 70% of interns switch the industry between the internship and their first regular employment.

Table A8: Individuals switch industries between internship and first employment

	Internship		1st job	
Industry	Freq.	Percent	Freq.	Percent
other services	79	14.16	379	8.90
Media	53	9.50	88	2.07
Engineering office	39	6.99	247	5.80
Health sector	39	6.99	391	9.18
Machine/ Car building	31	5.56	251	5.89
social services	28	5.02	191	4.48
Arts, Culture	26	4.66	70	1.64
Publishing	25	4.48	37	0.87
Public Administration	25	4.48	196	4.60
Law / Economic Consulting	21	3.76	139	3.26
Political Parties, Organizations	21	3.76	63	1.48
Manufacturing	19	3.41	101	2.37
Construction	19	3.24	70	1.64
Research Institutions	17	3.05	141	3.31
Banking	14	2.51	84	1.97
Universities	11	1.97	521	12.23

Note: Non-exhaustive list of industries. The left-hand side of the table is sorted in decreasing order of internship frequency.