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The impact of trade, offshoring and multinationals on job loss and job finding[1]

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Abstract

A commonly expressed concern is that offshoring of jobs to less developed countries coupled with technological progress may lead to job and wage polarization in developed countries. We use matched firm worker data to assess the impact of globalization processes on labor market outcomes. Females, younger workers and foreign-born workers are more likely to become unemployed. After controlling for worker and firm heterogeneity, we find no evidence for a statistically significant relationship between exporting, working for a foreign firm and having an offshorable job and unemployment. Clear evidence for the impact of offshoring on unemployment incidence is absent. Furthermore, exposure to globalization prior to getting unemployed is unrelated to the probability of finding a new job.

Keywords: unemployment, offshoring, globalization, duration models, labor market transitions.

JEL codes: J64, J62, F16.

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1. Introduction

The ongoing integration of the world economy has given rise to concerns about labor market impacts among politicians and the general public. The great recession has exacerbated these concerns, resulting in widespread public attention for multinational firms that were downscaling operations, the supposed danger of firms losing market share due to competition from the BRIC countries, and employees losing their jobs due to outsourcing. The general consensus that international trade in products and tasks is beneficial for the average individual does not necessarily imply that it is good for everyone. The effects on workers with different levels of education, or different industries and occupations, are far from trivial. The general consensus among economists regarding the long-run positive effects on higher productivity, increased incentives to innovate, and higher economic growth (see Crino, 2008; Grossman and Rossi-Hansberg, 2008) does by no means exclude the possibility that there are some transition effects along the way.

This paper aims to answer two questions. First, we estimate the extent to which the probability to become unemployed is related to different dimensions of globalization and worker characteristics. Second – in case an individual has been fired – we estimate how unemployment duration is related to the interaction of globalization (related to the old job) and worker characteristics. We devote attention to the impact of several dimensions of globalization, which are exporting behavior of firms, offshoring, and the presence of multinational companies.

Empirical evidence shows that the task composition of occupations has changed substantially during recent decades (Borghans and Ter Weel, 2006), and that the observed trend of increased fragmentation and internationalization of production processes could be a major explanation behind increased wage inequality and polarization – wage and employment growth at both the top and the bottom of the labor market while the middle lags behind – in some countries (Autor et al., 2006; Goos et al., 2009; Van Reenen, 2011; Fortin et al., 2011). Furthermore, while aggregate wage inequality has not changed much in the Netherlands during the last decade, trends in wage inequality show substantial heterogeneity between different types of workers (Groot and De Groot, 2011). This heterogeneity could be related to globalization.

While the public fear for these transitional effects is related mostly to unemployment, the empirical literature has focused largely on aggregate employment, and wages (e.g., Feenstra and Hanson, 1996; Autor et al., 2003; Crino, 2010; Goos et al., 2009). Studies that address the relationship between globalization and unemployment at the individual level are scarce (e.g., Egger et al., 2007; Munch, 2010). This paper aims to fill this gap in the literature by following individual workers over time and by investigating the factors that affect job loss and job finding. By applying Cox proportional hazard models and Cox regression models (Cox, 1972) – which are tools for duration and survival analysis – we estimate the effects of these three dimensions of globalization on job-to-unemployment and unemployment-to-job transitions. By combining several large Dutch micro datasets, we are able to relate worker characteristics and employment characteristics to the probability of unemployment and employment in a new job. Our data set includes the full employment record of workers, containing information on wages in previous and current jobs as well as number of days spent unemployed.

This paper is organized as follows. Section 2 reviews the recent literature on globalization and unemployment specifically focusing on research conducted at the individual level. The next section explains the data in detail and presents summary statistics and stylized facts. Section 4 discusses our empirical strategy and the following section presents the results of the empirical estimations. Section 6 concludes.

2. Globalization and unemployment

There is a clear link between the three indicators for globalization – offshoring, multinationals, and export activities – that we take into consideration.[2] Even though the activities of multinationals could be limited to strictly horizontal multinational activities (for example, to evade trade barriers and transportation costs), an important part of the activities of multinationals involves vertical interdependencies where each location is specialized in certain tasks according to local comparative cost advantages. This vertical component involves both the relocation of tasks, and trade linkages when intermediate products are shipped between subsidiaries. Offshoring can also take place outside multinationals, although in that case international trade is still involved. Activities of multinationals, international trade, and offshoring, are thus all related to the international division of labor and specialization according to comparative cost advantages.

In total, the Dutch input-output table for 2009 (as published by Statistics Netherlands) shows that 62 percent of Dutch imports (excluding imports that are transferred or re-exported) are used as intermediary inputs, while only 38 percent consists of final goods. Empirical evidence shows that the importance of imported intermediaries as a share of the total use of non-energy intermediaries – which is often used as a raw indicator for offshoring – is increasing across virtually all industrialized economies (Crino, 2008). Apart from international task specialization, export activities can be considered as a proxy that indicates the extent to which firms face foreign competition.

[2] Even though the use of imports by firms is at least as relevant as exports, we have to limit this paper to exports as the only trade measure, due to a lack of data on imports by firm.

There has been a recent surge of interest in the labor market effects of globalization. As early as the 1990s, researchers studied the role of international trade and increasing imported inputs on employment and productivity (e.g., Feenstra and Hanson, 1996 and 2001; Brainard and Riker, 1997; Anderton and Brenton, 1999). The recent literature argues that the globalization processes, together with advances in technology, has resulted in job and wage polarization.

Relatively simple extensions of Heckscher-Ohlin and Stolper-Samuelson trade models predict increased demand for the abundant factor (which are tasks that require high skilled labor), and a shift in relative factor prices that increases the wages of high skilled workers. Contrary to the expectations of the basic Heckscher-Ohlin arguments, this trend is also observed in less developed countries (Goldberg and Pavcnik, 2007).

In contrast, the task-based literature argues that technological advancements permit the breaking up of jobs into small pieces of tasks, such that offshoring affects employment through its effects on task demand rather than on demand for low skilled versus high skilled workers (Grossman and Rossi-Hansberg, 2008). The skill biased technological change (SBTC) literature argues that technology complements skills, which implies that skilled labor demand and wages increase at the expense of low-skilled jobs (Acemoglu, 1998; Berman et al., 1998). Autor et al. (2003) argue that the decrease in the demand for manual routine tasks may explain job polarization in the US. The main argument of the task-based explanations of polarization is that some tasks are separable from the occupation bundle (which is defined as the set of tasks that composes an occupation), which later can be offshored to low-wage locations (e.g., Blinder, 2009; Akçomak et al., 2011).

The empirical evidence regarding these theories is mixed. Some researchers have found evidence that is consistent with a negative relation between offshoring and job and wage polarization (e.g., Feenstra and Hanson, 2001; Scheve and Slaughter, 2004; Crino, 2010; Baumgarten et al., 2010; Fortin et al., 2011; Goos et al., 2009), while others found negligible or zero effects (Amiti and Wei, 2005; Mankiw and Swagel, 2006; Liu and Trefler, 2008; Koller and Stehrer, 2009; Criscuolo and Garicano, 2010).

The empirical literature discussed above mostly relies on aggregate data at the industry or occupation level. Only few studies employed worker level data to assess the impact of the globalization process on employment. These studies have combined industry level offshoring measures with individual level data, which makes it possible to follow workers for a specific time period.[3] Researchers investigated the impact of offshoring on job displacement in general and transitions to unemployment, weeks spent

[3] Most studies use measures that are similar to those introduced by Feenstra and Hanson (1996), where offshoring is proxied by the intermediate imported inputs as a share of total inputs.

unemployed between two jobs and earnings differentials in particular. This strand of literature is related to previous research on job turnover at the worker level (e.g., Royalty, 1998; Gomes, 2012). One of the first studies that assesses the short-run employment effects of offshoring in a longitudinal setting is the work of Egger et al. (2007). Using Austrian data between 1998 and 2001, they estimated a dynamic fixed effect multinomial logit model. They find that offshoring reduces the probability to remain in the manufacturing sector, as well as the probability of switching to the manufacturing sector.

Liu and Trefler (2008) have used US data from 1996 to 2006 to assess the impact of offshore outsourcing in the service sector to India and China on four labor market outcomes. They consider switching of employees between industries, occupation switching, number of weeks spent unemployed, and the earnings difference between two jobs. They find small negative or zero effects of offshoring on all labor market outcomes that were taken into consideration. These results validate earlier findings of Ebenstein et al. (2009), regarding the small negative impact of offshoring to low wage countries on employment levels in US.

In a later study for the years 1996 to 2007, Liu and Trefler (2011) differentiated between upward and downward switching (i.e., switching to an occupation that pays less on average). They find that the cumulative 10-year impact of imports of services from India and China caused downward occupation switching to rise by 17 percent and transitions to unemployment to rise by 0.9 percentage points. In the studies above, much of the negative impact of offshoring on earnings is observed when workers in the manufacturing sector had to switch to a job in services that pays less on average.

Within the existing empirical literature, the study that is perhaps closest to our approach is Munch (2010). He used Danish manufacturing sector data from 1990 to 2003 to investigate the effect of offshoring on short-run job displacement. The research focuses on unemployment spells that end with a transition into a new job and considers three outcomes: occupation switching, job to unemployment and job to non-participation transitions. They find that there are small effects of offshoring on unemployment. Offshoring increases the unemployment risk by 1 percent. However, this effect is much larger for men, workers above 50 and low-skilled workers.

We assess the short-term relationship between offshoring and unemployment duration using longitudinal data at the worker level. Egger et al. (2007) have used a similar setting, but controlled only for age thus failing to account properly for worker heterogeneity. Munch (2010) estimated a duration model controlling for various individual characteristics such as age, education and gender. One of the contributions of this paper is that we not only estimate job-to-unemployment transition, but unemployment-to-job transitions as well. Offshoring and other individual characteristics may increase unemployment duration and at the same time may decrease the probability of finding a new job. For instance our estimates reveal that foreign workers are more likely to become unemployed and once they are unemployed they are also likely to remain unemployed for a much longer time.

3. Data and stylized facts

Data

This paper uses micro data that are available through Statistics Netherlands (CBS). For data on worker characteristics – like date of birth, gender, country of birth, and the wage – we rely on tax data reported by employers, available through the CBS Social Statistics Database (SSB, *Sociaal Statistisch Bestand*). We use two branches of SSB, one regarding jobs (*SSB Banen)* and one regarding unemployment benefits (*SSB WW*). Of each job, we have the exact date when a worker starts working for a certain establishment of a firm, and (if this applies) the date when the job ends. As this dataset covers all Dutch employees and firms with employees, we use this data source to calculate the number of employees per firm and per municipality. Data are available for 2000–2008. Country of birth is used to determine whether a worker is native, non-native born in a developed country (with at least a GDP of US$ 20,000 in 2010),[4] or non-natives born in any other country.

For each person with unemployment benefits, we use the codified social security number combined with the date when the person was first entitled to unemployment benefits – as well as the date when entitlement ended – to match unemployment benefits to the end date of the previous and (if applicable) the starting date of the next job. The unit of observation is thus a job of an employee that may or may not end in unemployment. Even though the cause of unemployment is unknown, it has to be involuntary, since only involuntary unemployed are entitled to unemployment benefits according to Dutch law. Because the registration processes of the end date of a job and the start of entitlement to unemployment benefits are independent (and rather imprecise, as turned out), we consider a merge successful if the difference between the two is at most two months.

[4] According to the World Economic Outlook Database of the International Monetary Fund these include Luxembourg, Norway, Qatar, Switzerland, Denmark, Australia, Sweden, the United Arab Emirates, the United States, the Netherlands, Canada, Ireland, Austria, Finland, Singapore, Belgium, Japan, France, Germany, Iceland, the United Kingdom, Italy, Kuwait, Hong Kong, New Zealand, Spain, Brunei, Cyprus, Greece, Israel, Slovenia, Portugal, the Bahamas and South Korea.

A rather large part of individuals that receive unemployment benefits, do not have a strong attachment to a previous job. Some workers have many succeeding jobs that do not last long, or multiple jobs at the same time, while others even seem to start receiving unemployment benefits when their job has not yet ended.[5] Including these workers would generate noise in the dataset for two reasons. First, the environment and occupation of the last job are not well defined. Second, it is well possible that workers who get unemployed frequently are fired not because of the characteristics of their last jobs, but rather due to some (unobserved) worker characteristics. It is unclear in these cases that unemployment is related to globalization. To exclude this source of noise, we have limited our dataset to only those workers who were employed by only one single employer for at least two years prior to losing their job. When an unemployed worker has found a new job, we require that it lasts for at least two months before we consider it a successful exit from unemployment. Another difficulty is to obtain a good estimate of the last wage earned by an employee. As employees who get fired may receive a bonus when getting fired, this may result in an overestimation of their wage. We therefore use the fiscal wage of the year prior to getting unemployed. This implies that we do not include workers who entered unemployment in 2000 in our analyses, the first year for which we have data available, as their jobs cannot be observed in the year before they were fired.

To make wages comparable over time, we have corrected all wages for the change in average wage (the base year is 2008).[6] The wage differential between the wage of a worker prior to getting unemployed and the wage earned from the next job is thus based on the relative position of the worker in the wage distribution. Because we have no reliable indicator for hours worked (though we have an indicator for the number of *days* worked), we limit our dataset to jobs of at least 0.8 fte (fulltime employment equivalents). Finally, we exclude all employees younger than 20 or older than 60 (as they may enter into an early retirement schedule) when getting unemployed, and we have excluded all jobs earning less than the equivalent of the minimum yearly wage in 2008 (corrected for inflation). Table 1 shows the results of this matching process.

To compare workers who entered unemployment to workers who remained employed, we applied the same criteria to workers remaining employed. The resulting dataset includes 4.41 million employees (representing 35 percent of the total Dutch labor volume) working at some point in time during the 2000–2008 period. 163 thousand out of

[5] This can happen, for example, when the number of working hours of a worker with a flexible contract is reduced.

[6] The advantage of this approach compared to, for example, using real wages is that the wage difference between the last full year an individual worked prior to unemployment, and the first year in a new job, is not affected by growth in real wages. This is especially important as the time between jobs is not fixed.

those 4.41 million employees were fired at least once with the individual entitled to unemployment benefits, which accounts for 7.1 percent of total unemployment benefits. Even though our dataset is thus more or less representative for a typical full-time employee with a stable employment relationship, it is not representative for the typical unemployed. Information about the last known job is a necessary condition when estimating the effect of characteristics of this job on job-loss. Furthermore, it is likely that the determinants of job-loss of workers outside our sample are at least to some extent similar to the determinants of job loss of workers with similar observed characteristics that are in our sample. It is possible that workers outside our sample have less favorable unobserved characteristics, or that the lack of stability in the employment records of the workers outside our sample itself is caused by globalization, but this falls beyond the scope of this paper.

Table 1. Results of matching jobs to unemployment benefits

Year	New entrants entitled to unemployment benefits	Successfully merged to a job of at least 0.8 fte, paying at least minimum wage during the previous 2 years	
2001	224,055	10,474	4.7%
2002	279,697	20,051	7.2%
2003	358,049	27,294	7.6%
2004	370,517	31,459	8.5%
2005	332,913	27,702	8.3%
2006	287,179	18,101	6.3%
2007	245,423	15,124	6.2%
2008	203,750	13,949	6.8%
Average	287,698	20,519	7.1%

Table 2 presents descriptive statistics concerning key variables of interest for workers that had at least one job between 2001 and 2008, while never being unemployed (left column), as well as for workers who experienced at least one episode of unemployment during the same period. Workers who enter unemployment are somewhat younger than the average employee in our sample. Furthermore male workers and non-natives (both those born in developed and those born in developing countries) are substantially overrepresented in the group of workers who have experienced unemployment. An interesting finding that emerges from Table 2 is that almost 20 percent of workers that experienced unemployment had been previously working at a foreign firm, while less than 14 percent of all workers who were never unemployed worked at a foreign firm.

Table 2. Descriptive statistics of workers and unemployed, 2001–2008

	Never unemployed	Unemployed at least once
Observations (*N*)	4,245,683	163,091
Age	43.30	42.58
	(10.61)	(9.78)
Female	0.280	0.239
	(0.449)	(0.427)
Non-native (developed)	0.024	0.032
	(0.152)	(0.175)
Non-native (other)	0.070	0.118
	(0.255)	(0.322)
Last wage	42,957	41,731
	(24,457)	(23,819)
Foreign firm	0.138	0.197
	(0.345)	(0.398)

Notes: Standard deviations are in parentheses. All differences are statistically significant at significance levels far beyond 0.001.

Stylized facts by industry, level of education, and occupation

Table 3 presents a number of descriptive statistics by industry. All data on industries and firms relates to the job an individual had *before* getting unemployed. The highest incidence of unemployment can be observed among workers that were previously employed in the manufacturing industry, where 3.6 percent of the workforce has received unemployment benefits at least once. In manufacturing, workers are much more often fired during mass layoffs compared to any other industry.[7] Workers in other private industries have a lower probability to become unemployed, generally between 2 and 3 percent. The lowest incidence of unemployment is observed in public services, particularly amongst government employees.

There is no strong relationship between the incidence of unemployment and average unemployment duration. However, unemployment duration of individuals that were fired from a manufacturing job is notably higher than in all other industries (except for the relatively small mining sector), indicating relative difficulty in the job search process. There is a strong (negative) correlation between average unemployment duration within industries and the share of unemployed that will eventually succeed in finding a new job. The largest average wage differential between the job prior to unemployment and the next

[7] We define a mass layoff as a situation in which at least 20% of the work force is being fired in a single year for firms with 20 or more employees (prior to the layoff), 40% for firms with 10 to 20 employees, and 60% for firms with 5 to 10 employees. The reason to use a somewhat higher percentage for smaller firms is that in small firms 20% of the work force corresponds to just a few employees. Though this definition is somewhat arbitrary, it could be interesting to see whether lay offs are rather random within industries, or whether they are concentrated in some firms.

job is found for construction workers, who earn about 6 thousand euro less. Workers who were employed within the education sector, on the other hand, gain about 8 thousand euro annually if they succeed to find a new job.

Table 3. Descriptive statistics by industry, 2001–2008

	# Observations	Average annual fiscal wage (all workers)	% Unemployed at least once	Average unemployment duration (months)	% Of unemployed that finds a new job before 2009	Average wage differential*	% Share of mass layoffs in total layoffs
Agriculture	82,447	34,354	2.04	10.5	75.9	–16	2.9
		(13,088)		(15.5)		(9,624)	
Mining and quarrying	10,894	73,394	1.94	15.1	70.1	–3,410	4.3
		(40,712)		(19.5)		(25,404)	
Manufacturing	1,152,705	42,163	3.63	14.9	71.4	–2,286	18.6
		(21,662)		(18.2)		(13,251)	
Construction	536,943	40,355	2.95	10.7	75.6	–6,238	6.3
		(14,842)		(15.4)		(9,644)	
Trade	637,211	43,826	3.30	11.3	77.8	–562	5.1
		(27,075)		(14.8)		(16,306)	
Hotels and Restaurants	101,734	31,972	3.05	9.1	79.8	–842	1.7
		(15,118)		(11.6)		(9,769)	
Transport	490,893	42,725	2.21	13.3	71.7	–2,293	4.3
		(22,439)		(16.7)		(16,313)	
Commercial services	1,330,582	53,256	2.73	11.9	76.4	–381	4.3
		(34,414)		(15.0)		(18,113)	
Government	671,872	43,196	0.64	11.7	72.5	–1,662	0.6
		(15,159)		(16.0)		(10,787)	
Education	362,978	42,401	1.64	13.0	63.1	8,122	0.8
		(14,279)		(16.9)		(13,190)	
Healthcare	547,297	37,868	1.62	11.1	70.8	1,466	2.5
		(19,074)		(13.0)		(14,619)	
Other	197,589	40,861	3.33	11.5	72.0	–366	3.9
		(22,228)		(14.4)		(14,514)	
Total	6,123,175	44,155	2.56	12.5	73.8	670	8.0
		(24,619)		(16,1)		(15,121)	

Notes: standard deviations are in parentheses. *Compares the normalized annual fiscal wage differential between the job prior to unemployment and the job after unemployment. Differentials larger than 100,000 euro's are excluded.

Additional data on worker characteristics (viz. education and occupation on the 2-digit Statistics Netherlands occupation classification) are drawn from different cross-sections of the annual labor market survey (EBB, *Enquête Beroeps Bevolking*), 2000–2008. We distinguish eight different levels of education and 90 different occupations. After merging the dataset with data on employees and unemployed – that was constructed as described above – with EBB, about 159 thousand observations remain (2 thousand of these jobs end in unemployment).[8]

Table 4 presents descriptive statistics by level of education. Indeed, workers with a university Master degree earn about twice as much as workers with only primary education. However, the relationship with unemployment is nontrivial. Even though workers with only primary education have the highest probability to get unemployed and have the highest average unemployment duration, workers with intermediate levels of tertiary education have the lowest probability to get fired and have the shortest unemployment duration. These two types of schooling are often focused on a specific (skilled) profession. Workers with a PhD or university Masters degree are somewhat in between on both accounts. The share of workers who find a new job before 2009 (e.g., within our period of observation) is average for individuals with the highest level of education, while it is much higher for individuals educated at the intermediate levels.

[8] Note that only 1.23 percent of the observed individuals is fired according to the dataset that resulted after merging with the labour force survey, whereas this figure was 2.56 percent prior to merging. This implies that workers with comparable jobs have a relatively smaller probability to be included in the labour force survey if they are fired at some point in time. The main explanation for this is that workers who are fired are only in the labor survey at a moment they were still employed when they were inverviewed *prior* to their being fired. If we assume that both the probability to be fired and the probability to be inverviewed at a certain day in a year are random, this results in an underrepresentation of workers who get fired. However, as this probability is unrelated to what determined their unemployment, it does not bias our results.

Table 4. Descriptive statistics by level of education, 2001–2008

	# Observations	Average annual fiscal wage (all workers)	% Unemployed at least once	Average unemployment duration (months)	% Of unemployed that finds a new job before 2009	% Share of mass layoffs in total layoffs
Primary education	7,651	34,634	1.56	16.3	66.4	16.0
		(11,729)		(18.7)		
Lower secondary education (VMBO, MBO 1)	8,132	38,338	1.71	15.5	67.6	10.1
		(17,735)		(18.8)		
Lower tertiary education (MBO 2, 3)	26,703	38,329	1.22	11.8	74.8	7.1
		(13,562)		(16.2)		
Lower tertiary education (MBO 4)	33,837	41,286	1.06	9.6	80.7	7.8
		(16,213)		(12.7)		
Higher secondary education (HAVO, VWO)	11,137	44,906	1.39	11.2	81.9	7.1
		(23,009)		(13.0)		
Higher tertiary education (HBO, BA)	33,257	52,070	1.05	11.3	75.1	3.1
		(23,956)		(13.3)		
Higher tertiary education (MA, PhD)	17,721	68,414	1.21	11.6	76.2	2.8
		(38,982)		(14.3)		
Total	159,170	45,158	1.23	10.7	75.6	7.3
		(23,501)		(12.4)		

Note: Standard deviations are in parentheses.

Table 5 presents key statistics on unemployment for workers previously employed in 24 different 2-digit ISCO 88 occupations. Not surprisingly, there are substantial differences between occupations. Teaching professionals (ISCO 23) and life science and health associate professionals (ISCO 32) have the lowest unemployment incidence. Within our dataset, unemployment is observed for only 0.3 to 0.4 percent of the employees with these occupations. Occupations with the highest unemployment incidence are precision, handicraft, craft printing and related trade workers (ISCO 73), followed by machine operators and assemblers (ISCO 82).

Table 5. Descriptive statistics by 2-digit ISCO 88 occupation, 2001-2008

	# Observations	Average annual fiscal wage (all workers)	% Unemployed at least once	Average unemployment duration (months)	% Of unemployed that finds a new job before 2009	% Share of mass layoffs in total layoffs
12. Corporate managers	15,967	62,308 (37,838)	1.42	12.4 (15.5)	71.4	8.4
13. Managers of small enterprises	6,055	59,488 (35,633)	1.39	12.0 (13.6)	70.2	1.2
21. Physical, mathematical and engineering science professionals	9,374	55,974 (21,967)	1.23	9.5 (12.3)	82.6	7.0
22. Life science and health professionals	2,172	60,199 (35,385)	0.78	10.1 (11.1)	*	*
23. Teaching professionals	7,435	46,410 (13,696)	0.32	19.0 (24.8)	*	*
24. Other professionals	7,131	52,602 (25,466)	1.67	12.6 (13.2)	69.7	1.7
31. Physical and engineering science associate professionals	9,622	45,695 (20,417)	1.05	13.5 (19.3)	74.3	10.9
32. Life science and health associate professionals	4,170	34,375 (9,416)	0.38	8.1 (11.1)	*	*
34. Other associate professionals	14,165	45,516 (21,333)	1.15	13.4 (15.8)	74.2	2.5
41. Office clerks	11,627	38,033 (13,527)	1.26	13.3 (17.0)	78.9	2.7
42. Customer services clerks	1,613	31,870 (11,949)	1.74	11.0 (14.5)	*	*
51. Personal and protective services workers	5,751	34,284 (12,890)	0.90	12.9 (15.8)	63.5	0.0
52. Models, salespersons and demonstrators	4,335	38,027 (20,306)	1.48	9.9 (11.3)	85.9	0.0
61. Skilled agricultural and fishery workers	2,084	30,435 (8,056)	0.86	7.1 (10.5)	*	*
71. Extraction and building trades workers	9,431	36,596 (7,880)	1.86	9.0 (14.3)	83.3	8.0
72. Metal, machinery and related trades workers	9,338	36,723 (9,443)	1.18	11.5 (15.4)	80.0	14.5
73. Precision, handicraft, craft printing and related trades workers	905	36,036 (9,867)	2.32	17.8 (18.4)	*	*
74. Other craft and related trades workers	1,430	32,496 (18,721)	1.61	6.4 (5.9)	*	*
81. Stationary plant and related operators	1,964	45,241 (13,885)	0.87	11.8 (9.6)	*	*
82. Machine operators and assemblers	4,224	34,893 (9,143)	1.92	12.9 (15.6)	77.8	33.3
83. Drivers and mobile plant operators	7,760	37,444 (8,180)	0.86	8.4 (11.8)	79.1	10.4
91. Sales and services elementary occupations	1,885	29,694 (7,750)	1.33	10.5 (11.0)	*	*
93. Laborers in mining, construction, manufacturing and transport	357	38,813 (8,237)	1.68	3.0 (2.5)	*	*
Total	138,820	44,964 (23,483)	1.22	11.7 (15.0)	75.4	7.4

Note: Standard deviations are in parentheses. * We report no results if less than 50 individuals in an industry were fired.

It has often been suggested that rigid labor markets in Europe have resulted in a more compressed wage distribution with higher unemployment (see, for example, Nahuis and

De Groot, 2003; Acemoglu and Newman, 2002). As the upward pressure from labor market institutions on wages is particularly large for lower paid jobs, this would be likely to result in higher unemployment in lower paid occupations, as wages are not allowed to sufficiently adjust to clear the labor market. However, this cannot be observed for the workers in our sample, as the correlation between the average wage within occupations and the risk of unemployment is close to zero.

There is also a substantial pool of workers who do not manage to hold steady jobs, or who are structurally unemployed, and are thus not the topic of the present paper. It is possible that one of the reasons of their unemployment is that the type of jobs they *could* have done has been outsourced. As this paper addresses only the transition from a job to unemployment (because we need to know the previous job to observe the covariates of individuals getting fired), we leave the quest for the determinants of this structural unemployment for future research. At the same time, however, we must note that what determines unemployment of individuals who were recently employed is likely to be related to what determines unemployment of those without steady employment records.

Employees fired from manufacturing have higher probability to find a new job, and relatively low average unemployment duration compared to many of the services industries. It is, however, likely that there are some selection effects in place. For workers with occupations where many individuals are fired, or where there are relatively many mass layoffs, worker's individual performance may be less related to the state of unemployment. On the other hand, when a police officer – working in an occupation where unemployment is relatively rare – is fired, this may be more likely due to personal characteristics, which may make it more difficult to find a new job.

Indicators for trade, offshoring and activities of multinationals

We use three measures for exposure to globalization. The first is foreign ownership of firms. On the firm level, we determine whether a firm is foreign owned or not, using the Statistics Netherlands indicator on the home country of the Ultimate Controlling Institute (UCI) of each firm. This indicator draws on multiple data sources. It is important to note that subsidiaries of foreign firms can be considered part of a multinational firm, but do not cover Dutch owned firms that have activities in multiple countries. Also on the firm level, we have used the Dutch production Statistics to calculate exports as share of total turnover, which is our second indicator for globalization. For our third measure, offshoring, we use four different and detailed indicators, which have been constructed for 374 occupations (on the 4-digit ISCO 88 level).

Three of these indicators are based on the O*NET database, a database developed for the US Department of Labor on the nature of work, as well as required skills, abilities and knowledge for 862 US occupations.[9] Many recent papers that use the task content of jobs and offshorability rely on this database (Goos and Manning, 2007; Goos et al., 2009; Crino, 2010; Blinder, 2009; Fortin et al., 2011). A concordance table has been used to map the SOC classification to the ISCO 88 classification. Autor et al. (2003) use the Dictionary of Occupational Titles (DOT), which is the predecessor of O*NET to construct a measure of routine vs. non-routine occupations. We use a routine measure similar to that developed by Fortin et al. (2011) “in the spirit of Autor” (Fortin et al., 2011, pp. 11), using the “degree of automation”, “importance of repeating same tasks”, “structured versus unstructured work”, “pace determined by speed of equipment” (which are variables that are included in the O*NET database).

Our second offshoring indicator captures face-to-face contact. The need for face-to-face personal contact is a key determinant of the offshorability of jobs (Blinder, 2009; Fortin et al., 2011), as jobs that require regular meetings with customers (e.g., doctors, social workers, sales persons) cannot be offshored. Our face-to-face index is similar to the one used by Jensen and Kletzer (2010) and Fortin et al. (2011), using “coaching and developing others”, “face-to-face discussions”, “assisting and caring for others”, “performing for or working directly with the public” and “establishing and maintaining interpersonal relationships”.

The information provided by the O*NET database is not suitable to capture another defining characteristic that determines whether a job is bound to a specific location: the importance of proximity. Both the task routine index and the face-to-face index therefore consider jobs such as cleaners, construction workers, mail carriers and garbage collectors to be quite offshorable. Hence, Blinder (2009) creates a subjective classification of offshorability, using the job descriptions and characteristics of O*NET, but applying subjective judgment rather than mathematical rules. We use the resulting Blinder index as third indicator for offshorability. As this data is also reported using the SOC classification, we use a concordance table to map it to the 4-digit ISCO 88 level. As the Blinder index is unavailable for some occupations, this results in a dataset with about 240 occupations, thereby reducing the number of observations somewhat.

To combine the advantages of an objective mathematical classification while at the same time addressing some of the critique on such measures, we have created a new offshorability measure that combines the O*NET based routine task and face-to-face indexes with a subjective list of occupations that are bound to a specific location. While the overall offshorability of occupations is rather difficult to observe – which makes a subjective ranking difficult to reproduce (see, for example, Blinder, 2009) – we argue that

[9] This database is available at http://online.onetcenter.org.

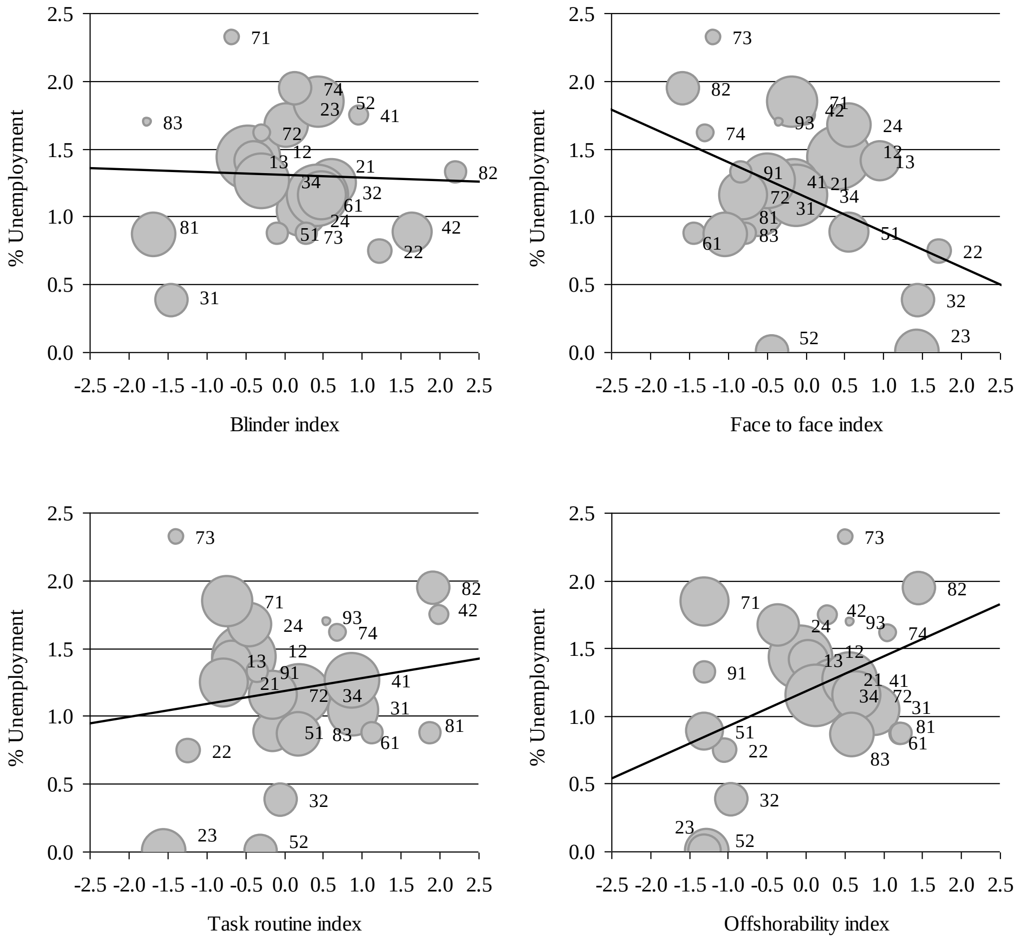
making a list of occupations that are non-tradable because of an inherent need to be performed at a specific location is rather straightforward. This list includes 112 occupations, such as waiters, plasterers, haircutters, police officers, government officials, cleaners, medical personnel, library clerks, and athletes.

We consider only occupations that are tied directly to the *end user* as being tied to a location. For example, it is not clear how different a farmer is from a factory worker in terms of being tied to a specific location. While it may be true that (as Blinder, 2009, argues) the work at a specific piece of US land cannot be done from abroad, the same holds for the work inside a specific US factory. However, both agricultural and manufactured products can be traded, and the domestic production and employment structure may change accordingly. Our offshorability indicator is constructed as follows. We start by normalizing the task routine and face-to-face indexes (to a 0 mean and 1 standard deviation). Subsequently, we subtract the face-to-face index (which is a negative offshorability index) from the task routine index, and standardize the result between 0 (least offshorable) and 1 (most offshorable). Changing offshorability of all occupations that are bound to a location to 0 results in our offshorability indicator.

The four panels of Figure 1 relate the different offshoring indicators to the probability of becoming unemployed. The size of the circles reflects the share of each occupation in total employment in our dataset. There is no apparent relation between the Blinder index and unemployment. In contrast, the importance of face-to-face contact – which is presented in the second panel of Figure 1 – is clearly associated to less unemployment (with a correlation coefficient of –0.42). Task routine is associated to higher unemployment, though this relation is not as strong as was the case for face-to-face contact (correlation 0.17). Our overall offshorability index associates higher offshorability to higher unemployment, with a correlation coefficient of 0.42.

It has been argued that many lower paid occupations are not easily offshored or replaced by technology (see, for example, Autor et al., 2003 and 2006). While occupations with many routine tasks are generally occupations that pay low average wages (correlation –0.43), and occupations that require face-to-face contact are generally higher paid occupations (correlation 0.56), combining those two indicators and correcting for occupations that are location bound results in an offshorability index that is in fact negatively correlated to the average wage (correlation –0.10). Indexes that are highly correlated to other (favorable) characteristics of occupations may find a negative relationship between pretended offshorability and unemployment due to omitted variable biases.

Figure 1. Share of workers becoming unemployed by offshorability of occupations, 2001–2008



Notes: Size of circles denotes total employment within each occupation. The occupation codes correspond to those in Table 5. All offshorability measures have been standardized at 0 mean and a standard deviation of 1.

Table 6 presents the exposure to different indicators for globalization for workers with different levels of education. Both the lowest and the highest educated workers are somewhat less likely to work in foreign owned firms. For exporting this pattern is opposite: workers with higher tertiary education have on average work in firms with a relatively high share of exports in turnover. For comparison, all four offshorability measures have been standardized at 0 mean and a standard deviation of 1. The Blinder index is generally higher for higher educated workers, implying that their jobs are generally more easily offshored. There is a strong relationship between both the importance of face-to-face contact, and task routine, and level of education: the least educated workers are far less likely to have face-to-face contact, and much more likely to do routine work, relative to educated workers. Our combined offshorability index is mostly unrelated to level of education. As some offshorability measures are highly correlated with the level of education, it is interesting to see whether our empirical section will reveal any interaction effects between globalization indicators and the level of education.

Table 6. Globalization indicators by level of education, 2001–2008

	Share of foreign firms in employment	Average share of exports in turnover	Average of Blinder index	Average of face-to-face index	Average of task routine index	Average of offshorability index
Primary education	14.2	24.7	–0.394	–0.635	0.387	0.200
	(32.9)	(32.6)	(1.12)	(0.81)	(0.99)	(1.09)
Lower secondary education (VMBO, MBO 1)	13.7	24.3	–0.237	–0.523	0.210	0.119
	(34.3)	(32.7)	(1.07)	(0.82)	(0.99)	(1.07)
Lower tertiary education (MBO 2, 3)	12.6	25.9	–0.086	–0.200	0.106	–0.021
	(33.2)	(34.6)	(0.94)	(0.96)	(0.97)	(1.05)
Lower tertiary education (MBO 4)	14.3	23.5	0.055	–0.044	0.130	0.116
	(35.0)	(33.2)	(0.99)	(0.95)	(0.92)	(0.96)
Higher secondary education (HAVO, VWO)	15.5	23.6	0.100	0.051	0.280	0.101
	(36.2)	(33.3)	(0.97)	(0.94)	(0.93)	(0.97)
Higher tertiary education (HBO, BA)	13.3	27.2	0.087	0.473	–0.370	–0.165
	(34.9)	(34.7)	(0.97)	(0.95)	(0.98)	(0.93)
Higher tertiary education (MA, PhD)	12.3	28.2	0.132	0.626	–0.580	–0.292
	(32.9)	(34.7)	(0.96)	(0.93)	(0.90)	(0.89)
Total	13.6	25.1	0.000	0.000	0.000	0.000
	(34.2)	(33.7)	(1.00)	(1.00)	(1.00)	(1.00)

Note: Standard deviations are in parentheses.

4. Empirical methodology

This section uses Cox proportional hazard models and Cox regression models (Cox, 1972) to estimate the impact of human capital and a number of variables that are related to internationalization on employment spells and unemployment spells. An overview of the methodology and application of duration and survival analysis can be found in, for example, Therneau and Grambsch (2001) or Klein and Moeschberger (2005). Even though the application of survival and duration models in economics is far from new, they are – with few exceptions (e.g., Munch, 2010) – not regularly applied in the empirical literature that focuses on the effects of offshoring, international trade, and multinational firms on unemployment. Part of the literature uses individual level unemployment data (such as Liu and Trefler, 2011), thus exploiting the possibilities offered by micro data, but apply probit or logit specifications in which the probability that a worker with certain characteristics will become unemployed is estimated. Duration models make much more efficient use of the available data, because they allow for a flexible relation between job spell and the probability that a worker gets fired (or is hired again).

The central variable used to model the transition from a job to unemployment is the exit or hazard rate *h*, which is in essence the conditional probability density function of becoming unemployed in the next short time interval Δt , given that one has been working in a job until time *t*:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t \mid t \geq T)}{\Delta t} . \tag{3}$$

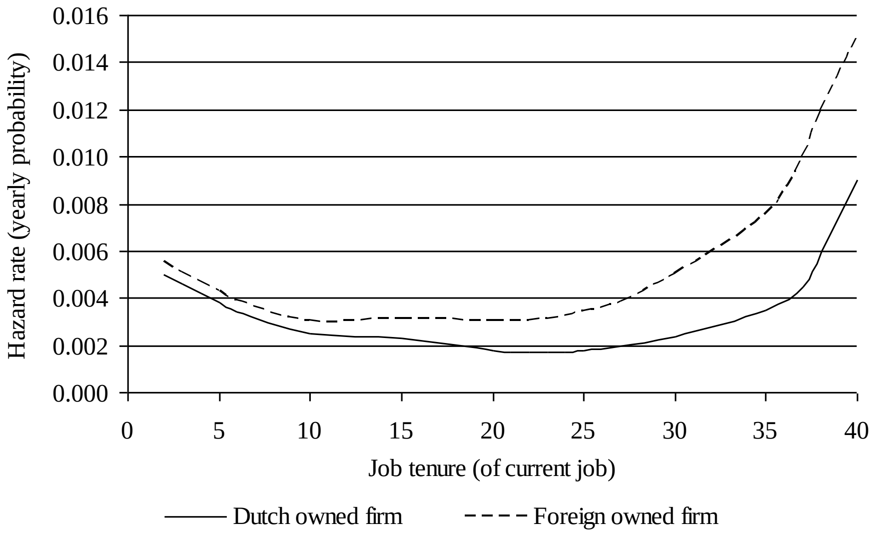
An increasing hazard rate implies a higher probability that an event occurs.

Figure 2 shows (as an example) the hazard time path for workers employed in Dutch owned firms, as compared to those working in foreign owned firms. On the horizontal axis is tenure (in years), on the vertical axis the probability to become unemployed at particular tenure. There is a substantial difference between Dutch and foreign firms: across the entire career the probability to enter unemployment is higher in foreign firms.

Throughout most of their careers, the probability of becoming involuntary unemployed is less than 0.5 percent per year. After about 25 years of service, the probability starts to increase, to about 1.5 percent.[10] This is a somewhat unexpected result, as the Dutch system is such that it becomes progressively more expensive to fire workers as they become older. Hassink (1999) and Gielen and Van Ours (2004) independently find that the probability to become unemployed increases for older workers in the Netherlands. Though they do not provide a full explanation for this phenomenon, it is attributed to the fact that older workers are relatively expensive, while their productivity decreases because of their – supposedly – out-dated knowledge and insufficient abilities regarding technological advancements (e.g., the so called efficient layoff rule of Lazear, 1995). As older workers experience relative difficulty to find a new job, it is likely that the probability that they will find a job in the months that pass between being informed about them being fired and actually being fired is lower as well. Furthermore, older workers are less likely to leave the firm in advance when they notice business is going bad. Therefore, the probability to be fired *and receive unemployment benefits* is likely to increase more than the probability to be fired.

[10] As a robustness check, we have estimated the econometric models in this section while excluding employees with a tenure that is above a certain number of years (20, 25, 30 and 35). This does not result in substantial changes in parameter estimates, which could be explained by the fact that the number of workers with a high tenure (e.g. above 20 years) is rather limited.

Figure 2. Hazard rates of the transition to unemployment



In duration analyses, the (natural logarithm of the) hazard rate is generally the dependent variable. The Cox (1972) proportional hazard model is a semi-parametric approach to estimate the effect of different covariates on the hazard rate. The base regression equation that is estimated in the next section, regarding the transition from a job to unemployment is:

$$\log h_i(t) = \alpha(t) + \beta_1 D_i^{female} + \beta_2 age_i + \beta_3 offshorability_i + \ldots + \beta_k x_i \,. \qquad (4)$$

The dependent variable is the natural logarithm of the hazard rate. The right hand side variables are a flexible base-hazard rate (which models the hazard rate as a function over time), and a number of covariates that enter the model linearly. The estimated model is semi-parametric, because while the baseline hazard function $\alpha(t)$ is unspecified and flexible, the other variables in the model are linear. The regression model is estimated using the partial likelihood estimator developed by Cox (1972). The interpretation of the estimated coefficients is that an increase in the value of the independent variable by one results in a change of the log hazard ratio by β, and thus a change in the hazard ratio by e^{β}. All coefficients reported in the next two sections are exponents of β, and can therefore be interpreted as hazard ratios. As we include a number of firm level variables in our regressions, the reported results are based on robust standard errors that are clustered within firms.

5. Empirical Results

Transition from employment to unemployment

This section applies the hazard models that were discussed in the previous section to estimate the impact of human capital and a number of variables that are related to internationalization on employment spells.

The dependent variable in this section is always the natural logarithm of the hazard rate (e.g., the hazard to become unemployed). We have estimated six different models. Model (I) is estimated without education or occupation variables. This gives us the advantage of a large number of observations. Model (II) repeats the estimation of model (I) for workers that are present in the labor force survey, and adds education dummies, while the models (III) to (VI) add our four occupation based offshoring indicators. Because of multicollinearity we estimate separate models for these indicators. Including our offshoring indicators slightly reduces the number of observations, as the job specification was not known for all workers in the labor force survey. Model (III) includes the Blinder index (Blinder, 2009). Model (IV) includes the face-to-face index, (V) the task routine index, and (VI) our combined offshorability index that takes into account both the need for face-to-face contact, task routine, and whether an occupation is bound to a specific location. For presentational reasons, we present the main results (Table 7), the estimated education dummies (Table 8) and industry dummies (Table 9) in separate tables.

The results indicate that women have a somewhat higher probability to become unemployed relative to males. In a given year, the probability is about 16 percent higher in specification (I) and – for unknown reasons – about 45 percent higher in all other specifications.[11] The finding that females are more likely to be fired is somewhat surprising. A possible explanation that would be consistent with this finding is that the variance in productivity of females (at a given wage offer) is larger compared to males. This would result in a larger fraction of females performing less than expected, which might be fired. Discrimination could theoretically also provide an explanation, but it is not clear why discriminating firms would first hire female employees to subsequently fire them. Productivity differences are unlikely to provide an explanation, as in that case this should also be reflected in wages.

Older workers have a substantially lower probability to become unemployed (after correcting for tenure, the reported parameter is an isolated effect of age). The effect of

[11] As a robustness check, we have also estimated equation (II) without education dummies, which implies estimating the specification of (I) on the population of (II). Except for gender, all estimates are robust. This implies that the relatively high female unemployment risk found in specifications (II) to (VI) is not explained by the addition of education, but rather due to sampling.

age is very robust across specifications. Foreign-born workers have a much higher probability to become unemployed than Dutch workers. The probability is about two-thirds higher for expats (which are born in advanced nations), and more than twice as high for other foreign workers. Even in the specifications that correct for level of education (non-western born immigrants are on average lower educated relative to natives), the probability of becoming unemployed remains far higher. Again, we suspect that the predictability of the productivity of workers might be related to this. In the case of foreign workers, it might also be a problem that they are less flexible compared to natives because of their lack of language skills. As was the case with the gender differential, the large difference between natives and foreign workers is an interesting topic for further research. If the probability to get fired is twice as large in a single year, the probability to get fired over a longer period of time will be a multiple of that. As this has consequences for the net fiscal contribution of foreign workers, it may have implications for policies that aim at attracting high skilled foreign workers. Even though substantial positive externalities are known to be associated to the presence of high skilled workers in general, the findings of this paper call for more thorough research into the specifics of foreign workers.

Workers who work at larger firms have a lower probability to become unemployed. Workers who are employed at foreign owned firms have a slightly higher probability to become unemployed (though this becomes statistically insignificant once we control for education), as have workers in firms that export relatively more. Workers who live in more densely populated areas have a lower probability to become unemployed.

We do not find any relation between the Blinder index and unemployment. This implies that having a job that is relatively easy to offshore – according to the ranking of Blinder (2009) – is not associated with a higher probability to become unemployed. Even though the stylized facts presented in Section 3, and in particular in Figure 1, showed that both the face-to-face index and task routine index are related to unemployment, the results in Table 7 indicate that almost nothing of this relation is left once we correct for other worker and job characteristics. Our combined offshorability index is negatively related to unemployment (e.g., higher offshorability of a job results in a lower probability of unemployment), although it is only marginally significant given the size of our dataset, particularly when compared to other determinants of unemployment.

Even though our estimation strategy could theoretically be affected by a number of estimation issues, these tend to result in an overestimation of the relationship between offshorability en unemployment incidence. For example, if many people who previously had a certain occupation have been fired, wages will go down which in turn makes offshoring less attractive due to reduced domestic wage costs. This negative feedback loop will result in an underestimation of the relation between offshoring and unemployment. However, our offshorability measures are derived from the task content of jobs and proximity rather than from actual offshoring activities on the level of the firm, and it seems unlikely that this task content or the importance of proximity are changing because of the level of unemployment. Selection effects could also potentially result in biased estimates. If employees notice that employment opportunities are reduced within a certain firm – due to globalization or because of other reasons – employees might try to find jobs elsewhere. As the most able employees are more successful in this, this could result in an overrepresentation of low quality employees in jobs where the probability to get fired is relatively high. The high unemployment hazard in these jobs may subsequently be partially explained by a relatively high share of low quality workers that have a ceteris paribus higher unemployment hazard and a part that is due to actual unemployment hazard. Again, this will result in an upward bias in the relation between offshorability and unemployment rather than in a downward bias. As we find hardly any relation between any of our globalization indicators and unemployment, suspecting that these potential estimation issues have a substantial effect on our estimates would imply that the dimensions of globalization that we analyze are in fact *reducing* unemployment.

Table 7. Estimation results for the transition to unemployment

Dependent: Log hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
# Observations	6,396,518	159,167	97,666	142,488	142,488	142,488
# Transitions to unemployment	164,136	1,950	1,336	1,767	1,767	1,767
Female	1.16***	1.45***	1.57***	1.46***	1.47***	1.46***
	(8.4)	(5.9)	(6.4)	(5.8)	(5.9)	(5.7)
Age	0.95***	0.95***	0.96***	0.96***	0.96***	0.96***
	(–28.5)	(–13.6)	(–10.8)	(–12.9)	(–12.9)	(–13.0)
Foreign born worker	1.75***	1.52**	1.48*	1.55**	1.55**	1.56**
from advanced country	(25.4)	(2.8)	(2.2)	(2.8)	(2.8)	(2.8)
Other foreign worker	2.23***	2.09***	2.31***	2.13***	2.13***	2.14***
	(52.8)	(8.5)	(8.5)	(8.3)	(8.3)	(8.3)
Blinder index			1.01			
			(0.2)			
Face-to-face index				1.03		
				(0.8)		
Task routine index					0.97	
					(–1.0)	
Offshorability index						0.93**
						(–2.5)
Log firm size	0.89***	0.87***	0.86***	0.87***	0.87***	0.87***
	(–14.8)	(–8.1)	(–8.4)	(–8.1)	(–8.0)	(–8.0)
Foreign firm	1.08***	1.11	1.16	1.17	1.17	1.17
	(4.5)	(1.0)	(1.4)	(1.5)	(1.5)	(1.5)
Share of export	1.56***	1.30	1.14	1.31	1.32	1.32
	(5.9)	(1.7)	(0.8)	(1.7)	(1.7)	(1.7)
Log residence density	0.96	0.91**	0.95	0.89***	0.89**	0.89**
	(–3.3)	(–2.6)	(–1.2)	(–3.1)	(–3.1)	(–3.1)
Education dummies (Table 8)	No	Yes	Yes	Yes	Yes	Yes
Industry dummies (Table 9)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***. For computational reasons, clustered robust standard errors reported in column (I) are based on subsamples. We have calculated clustered robust standard errors for subsamples of 10, 20, 30, 40, 50 and 60 percent of the total sample, and extrapolated them to 100 percent. As the estimated parameters are more precise when estimated on the full sample, and do not depend on whether standard errors are clustered or not, we present estimated coefficients for the full sample.

The relationship with education – which is presented in Table 8 – is rather linear with modest statistical significance. Workers with lower secondary or tertiary education have the lowest probability to become unemployed. These are usually more practically oriented types of education, which aim at a specific profession (for example, electrician or nurse). University graduates, on the other hand, have the highest probability to become unemployed. Workers with only primary education are somewhat in the middle. As the wages of workers is strongly correlated to their level of education, these findings may indicate that the Dutch labor market is working rather efficient, such that demand and supply on the labor market is cleared by the wages rather than by unemployment.

Table 8. Estimation results for the transition to unemployment – education

Dependent: Log Hazard rate	(II)	(III)	(IV)	(V)	(VI)
Lower secondary education	0.91	0.97	0.91	0.91	0.91
(VMBO, MBO 1)	(–0.9)	(–0.2)	(–0.8)	(–0.8)	(–0.8)
Lower tertiary education	0.85	1.03	0.84	0.84	0.84
(MBO 2, 3)	(–1.5)	(0.2)	(–1.5)	(–1.5)	(–1.5)
Lower tertiary education	0.75**	0.82	0.75*	0.75*	0.76*
(MBO 4)	(–2.6)	(–1.4)	(–2.4)	(–2.4)	(–2.4)
Higher secondary education	1.05	0.98	1.09	1.10	1.11
(HAVO, VWO)	(0.4)	(–0.1)	(0.7)	(0.7)	(0.8)
Higher tertiary education	1.01	1.10	1.03	1.03	1.04
(HBO, BA)	(0.1)	(0.6)	(0.3)	(0.3)	(0.3)
Higher tertiary education	1.41**	1.42*	1.37*	1.37*	1.38*
(MA, PhD)	(2.7)	(2.2)	(2.3)	(2.3)	(2.4)

*Note*s: omitted category is primary education. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

Table 9 presents the coefficients that correspond to the industry dummies that have been estimated simultaneously with the results presented in Table 7 and Table 8. While the stylized facts presented in Section 3 indicated a substantially higher incidence of unemployment within the manufacturing industry, most of this difference disappears when controlling for worker and firm heterogeneity. Unemployment, however, remains rare within the public sector, and particularly among government employees. Employees working in commercial services are relatively likely to become unemployed. Interestingly, when including the Blinder index (specification III), this effect disappears.

Table 9. Estimation results for the transition to unemployment – industry

Dependent: Log Hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
Mining and quarrying	0.90	0.37	0.44	0.43	0.43	0.44
	(1.0)	(–1.4)	(–1.1)	(–1.2)	(–1.2)	(–1.2)
Manufacturing	1.27^{***}	0.96	0.89	1.00	1.00	1.03
	(4.3)	(–0.3)	(–0.7)	(0.0)	(0.0)	(0.3)
Construction	1.23^{***}	1.21	1.08	1.27	1.26	1.23
	(3.9)	(1.5)	(0.4)	(1.8)	(1.8)	(1.5)
Trade	1.16^{**}	1.10	1.06	1.15	1.14	1.17
	(2.9)	(0.8)	(0.3)	(1.1)	(1.0)	(1.2)
Hotels and Restaurants	1.21^{**}	1.31	1.29	1.35	1.36	1.30
	(3.2)	(1.3)	(0.9)	(1.4)	(1.5)	(1.3)
Transport	0.91	0.70^{*}	0.61^{*}	0.72	0.72	0.73
	(–0.8)	(–2.1)	(–2.2)	(–1.8)	(–1.8)	(–1.7)
Commercial services	1.46^{***}	1.29^{*}	1.09	1.36^{*}	1.36^{*}	1.38^{**}
	(7.6)	(2.1)	(0.6)	(2.4)	(2.5)	(2.6)
Government	0.35^{***}	0.20^{***}	0.17^{***}	0.19^{***}	0.19^{***}	0.19^{***}
	(–4.7)	(–6.9)	(–5.8)	(–7.0)	(–7.0)	(–7.0)
Education	0.97	0.47^{***}	0.83	0.43^{***}	0.43^{***}	0.42^{***}
	(0.9)	(–3.9)	(–0.7)	(–4.2)	(–4.2)	(–4.4)
Healthcare	0.73^{**}	0.52^{***}	0.58^{**}	0.56^{***}	0.57^{***}	0.55^{***}
	(–2.7)	(–4.1)	(–2.6)	(–3.4)	(–3.4)	(–3.6)
Other	1.53^{***}	1.47^{**}	1.40	1.57^{**}	1.57^{**}	1.58^{**}
	(7.5)	(2.5)	(1.8)	(2.9)	(2.9)	(2.9)

Notes: omitted industry is agriculture. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

Because it is widely acknowledged that effects of globalization could be different for higher versus lower educated workers, we have re-estimated some of the regressions whilst adding interaction terms between education and our globalization indicators. The regression coefficients for these interaction effects are presented in Table 10. Note that these results are based on different regressions than those in Table 7, Table 8 and Table 9. In contrast to, for example, Munch (2010) we do not find any evidence for interaction effects. This suggests that, consistent with the task-based literature, the relationship between globalization and unemployment is not conditional on the education level (if present at all).

Table 10. Interaction effects between education and globalization indicators

Dependent: Log Hazard rate	Share of foreign firms in employment	Share of exports in turnover	Average of Blinder index	Average of face-to-face index	Average of task routine index	Average of offshorability index
Lower secondary education	1.12	1.08	1.06	1.16*	0.99	0.93
(VMBO, MBO 1)	(0.6)	(0.3)	(0.8)	(2.0)	(–0.1)	(–1.3)
Lower tertiary education	1.11	1.12	1.14	0.96	1.03	0.95
(MBO 2, 3)	(0.6)	(0.4)	(1.7)	(–0.7)	(0.6)	(–0.8)
Lower tertiary education	0.90	1.24	1.05	0.96	0.90	0.89
(MBO 4)	(–0.6)	(0.7)	(0.7)	(–0.6)	(–1.6)	(–1.9)
Higher secondary education	1.35	0.87	0.97	1.03	0.95	0.83*
(HAVO, VWO)	(1.4)	(0.3)	(–0.3)	(0.3)	(–0.6)	(–2.0)
Higher tertiary education	1.17	1.59	0.89	1.07	0.93	0.94
(HBO, BA)	(1.0)	(1.9)	(–1.9)	(1.0)	(–1.1)	(–0.8)
Higher tertiary education	0.87	1.29	0.93	1.03	1.06	1.06
(MA, PhD)	(–0.6)	(0.8)	(–0.9)	(0.3)	(0.7)	(0.7)

Notes: omitted category is primary education. The effects of exporting and foreign owned firms are estimated by extending model (II) with interaction terms, the effects of offshorability, the Blinder index, and the task routine index are estimated by extending respectively (III) to (VI). *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

From unemployment back to a job

After considering the transition from a job to unemployment, we now apply the same methodology to explain unemployment duration. Because we now model the transition from unemployment back to a job, the hazard rate represents the probability that an employee finds a job in a given *month*. The average incidence rate is 5.8 percent per month. It is important to note that all job related characteristics – also those related to globalization – represent the job an individual had before getting fired.

The dependent variable in this section is again the natural logarithm of the hazard rate (e.g., the hazard to find a job). We have estimated six different models. Model (I) is again estimated on our full data set, without merging to the labor force survey for education or occupation variables. Model (II) adds education dummies, while model (III) includes the Blinder index (Blinder, 2009), (III) the face-to-face index, (V) the task routine index and (IV) our combined offshorability index. Again, all offshoring indicators have been standardized. The main results are presented in Table 11, the estimated education dummies in Table 12 and industry dummies in Table 13.

While we showed earlier that females have a relatively high probability to become unemployed, gender does not matter for unemployment duration. As is generally found in the literature, even though Section 5.2 showed that older workers have a relatively lower probability to become unemployed, once they are unemployed they have a lower probability to find a new job. Expats, and particularly foreign workers that were not born in advanced nations, have a substantially lower probability to find a new job. They are thus not only far more likely to become unemployed, once unemployed they are also likely to remain unemployed for a relatively longer time. Workers who worked for larger firms before getting unemployed have a somewhat lower probability to find a new job. Workers who were fired during a mass layoff have a relatively high probability to find a new job. It is likely that employees with low unobserved skills (which may have been unknown to the employer during wage negotiations) generally have a higher probability to be fired. During mass layoffs, however, unemployment is mostly exogenous to the abilities of the employee, which will result in a higher average ability of workers that were fired.

Table 11. Estimation results for the transition from unemployment to a new job

Dependent: Log Hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
# Observations	162,131	1,930	1,324	1,748	1,748	1,748
# Transitions to a new job	119,480	1,455	992	1,313	1,313	1,313
Female	1.00	1.00	1.01	0.99	0.96	0.97
	(0.0)	(–0.1)	(0.1)	(–0.2)	(–0.5)	(–0.4)
Age	0.95***	0.95***	0.95***	0.95***	0.95***	0.95***
	(–56.1)	(–15.9)	(–13.7)	(–14.9)	(–15.0)	(–15.2)
Expat	0.87***	0.76	0.74	0.73	0.74	0.72*
	(–7.9)	(–1.8)	(–1.7)	(–1.9)	(–1.8)	(–2.0)
Other foreign worker	0.75***	0.75**	0.77*	0.72**	0.72***	0.72***
	(–27.7)	(–3.1)	(–2.4)	(–3.3)	(–3.3)	(–3.3)
Blinder index			0.98			
			(–0.6)			
Face-to-face index				0.91**		
				(–2.6)		
Task routine index					1.08**	
					(2.5)	
Offshorability index						1.11**
						(3.2)
Log firm size	0.97***	0.95***	0.95**	0.96**	0.96**	0.96**
	(–5.2)	(–3.3)	(–3.0)	(–3.0)	(–3.0)	(–3.0)
Foreign firm	1.10***	1.01	1.08	1.02	1.01	1.01
	(3.8)	(0.1)	(0.8)	(0.2)	(0.1)	(0.1)
Share of export	0.87***	0.80	0.76	0.79	0.80	0.79
	(–2.8)	(–1.5)	(–1.6)	(–1.5)	(–1.5)	(–1.5)
Log residence density	0.97***	1.01	1.05	1.00	1.01	1.00
	(–5.1)	(0.2)	(1.0)	(0.1)	(0.1)	(0.1)
Fired during a mass layoff	1.10***	1.20	1.20	1.16	1.17	1.15
	(4.2)	(1.7)	(1.6)	(1.4)	(1.4)	(1.3)
Education dummies (Table 12)	No	Yes	Yes	Yes	Yes	Yes
Industry dummies (Table 13)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

The relationship between globalization and unemployment does not show a clear pattern. When correcting for the level of education, having worked for a foreign firm does not seem to have any effect. Workers who were previously employed at a firm with relatively high exports seem to have a somewhat lower probability to find a new job, but this effect is statistically insignificant in all specifications except (I). While offshorability of the previous job as measured by the Blinder index is almost completely unrelated to the probability of finding a new job, the face-to-face index, task routine index and combined offshorability index indicate that higher offshorability of the previous occupation (thus indicating that the occupation could be offshored more easily) results in a significantly higher probability to exit unemployment. This implies that offshorability is related to less difficulty, rather than more, to finding a new job once an individual has been fired. Even though this might seem somewhat unexpected on first sight, this could be explained by a less complex matching process for routine jobs and jobs that require little face-to-face contact. For instance, teaching professionals have rather specific skills and thus may have longer unemployment duration because it may be difficult to find a new job that matches their skills (see, for example, the work of Gathmann and Schönberg, 2010, on task specificity). The fact that certain jobs allow for a relatively simple match between employer and employee is likely to result in a *ceteris paribus* quicker transition back to a job domestically, while this simple matching also increases offshorability.

Table 12 shows the estimation results for the education dummies that were included in regression models (II) to (VI). Higher educated workers have a higher probability to find a job relative to lower educated. University graduates, however, do not have a higher hazard rate towards a new job than other workers with at least the highest level of tertiary education (MBO 4). This means that they experience more unemployment: they have a higher probability to become unemployed and once they are unemployed they do not find a job quicker than other workers with an above average level of education.

Table 12. Estimation results for the transition to unemployment – education

Dependent: Log Hazard rate	(II)	(III)	(IV)	(V)	(VI)
Lower secondary education	1.23	1.32	1.29	1.30	1.29
(VMBO, MBO 1)	(1.7)	(1.6)	(1.9)	(2.0)	(1.9)
Lower tertiary education	1.25	1.56**	1.26	1.29	1.29
(MBO 2, 3)	(1.8)	(2.6)	(1.7)	(1.9)	(1.9)
Lower tertiary education	1.47**	1.65**	1.47**	1.50**	1.48**
(MBO 4)	(3.1)	(3.1)	(3.0)	(3.1)	(3.0)
Higher secondary education	1.41*	1.72**	1.44*	1.43*	1.44*
(HAVO, VWO)	(2.3)	(2.9)	(2.4)	(2.3)	(2.4)
Higher tertiary education	1.41**	1.63**	1.50**	1.50**	1.45**
(HBO, BA)	(2.7)	(3.0)	(3.0)	(3.0)	(2.8)
Higher tertiary education	1.41**	1.50*	1.41*	1.40*	1.35*
(MA, PhD)	(2.6)	(2.3)	(2.4)	(2.3)	(2.1)

Notes: omitted category is primary education. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

Table 13 presents the estimated industry dummies. As the stylized facts presented in Section 3 indicated, employees that were fired from a job in education have a relatively low probability to find a new job. However, the effect is no longer statistically significant when reducing the number of observations and correcting for education. Other ex-public sector employees have somewhat less chances on the labor market as well. Apart from having worked in the government sector, it does not matter from what industry an individual was fired.

Table 13. Estimation results for the transition to unemployment – industry

Dependent: Log Hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
Mining and quarrying	0.91	2.84	3.28	2.80	3.09	2.75
	(–1.1)	(1.5)	(1.7)	(1.5)	(1.6)	(1.5)
Manufacturing	0.98	0.94	1.02	0.91	0.92	0.86
	(–0.8)	(–0.5)	(0.1)	(–0.7)	(–0.6)	(–1.2)
Construction	0.95	0.90	1.00	0.88	0.91	0.92
	(–1.8)	(–0.7)	(0.0)	(–0.9)	(–0.8)	(–0.6)
Trade	1.04	0.88	0.93	0.87	0.89	0.84
	(1.9)	(–1.0)	(–0.4)	(–1.0)	(–0.8)	(–1.3)
Hotels and Restaurants	1.01	0.99	1.17	1.01	0.99	1.00
	(0.2)	(–0.1)	(0.5)	(0.0)	(–0.1)	(0.0)
Transport	1.01	1.02	0.97	0.96	0.98	0.93
	(0.4)	(0.2)	(–0.2)	(–0.2)	(–0.1)	(–0.5)
Commercial services	0.99	0.96	1.02	0.96	0.97	0.93
	(–0.3)	(–0.3)	(0.1)	(–0.4)	(–0.3)	(–0.6)
Government	0.92	0.75	1.08	1.00	0.99	0.96
	(–1.6)	(–1.3)	(0.3)	(0.0)	(0.0)	(–0.2)
Education	0.75***	0.74	1.09	0.78	0.80	0.77
	(–7.0)	(–1.6)	(0.3)	(–1.2)	(–1.0)	(–1.2)
Healthcare	1.04	0.81	1.01	0.89	0.89	0.88
	(1.4)	(–1.3)	(0.0)	(–0.7)	(–0.7)	(–0.8)
Other	0.84***	0.62**	0.76**	0.65**	0.66**	0.63**
	(–6.2)	(–3.1)	(–1.3)	(–2.8)	(–2.7)	(–3.0)

Notes: omitted industry is agriculture. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

6. Conclusion

International trade, offshoring and the activities of multinationals are generally thought to result in increased productivity in the long run, because they allow for increased specialization and economies of scale. However, in the short run such forces of internationalization may have adverse labor market effects for some groups of workers.

This paper employs a large micro dataset of Dutch matched firm worker data to analyze the relationship between different dimensions of globalization and unemployment as well as subsequent job finding.

We find that females and foreign-born workers (who also have a lower probability to find a new job once unemployed) have a higher probability of getting fired, while older workers (at a given tenure) are somewhat less likely to become unemployed, but also less likely to find a new job when unemployed. Both the lowest educated workers (e.g. those with only elementary education) and university graduates have a somewhat higher probability to get unemployed.

Workers employed at exporting firms have a significantly higher probability of getting fired. The estimated relationship is, however, not very strong. Our estimates imply that an average worker has a 0.8 percent point higher probability of getting fired during a 10-year employment spell when the share of exports in total turnover goes up by 10 percentage point. We find some limited evidence for a higher unemployment incidence among workers employed at foreign owned firms, but its effect becomes insignificant once we control for human capital.

The estimated relationship between offshoring and unemployment risk consistently fails to associate offshorability to higher unemployment incidence. We find no statistically significant effect of the Blinder index (Blinder, 2009), the need for face-to-face contact, and task routine, while we find that a higher score on a offshorability index that combines face-to-face contact, task routine, and whether a job is bound to a specific location is negatively related to unemployment (though this effect is not strong). We do not find any evidence for interactions between international trade, offshoring, or activities of foreign forms and level of education on the risk of unemployment.

Without correcting for level of education of workers that have been fired, our data seem to suggest that individuals fired from foreign owned firms have a somewhat higher probability to find a new job, and those fired from firms with higher exports a somewhat lower probability. However, once we correct for level of education these effects disappear. While offshorability as measured by the Blinder index is unrelated to the probability to find a new job, our (three) other offshoring indicators indicate that employees fired from occupations that are relatively offshorable are somewhat more likely to leave unemployment. The findings thus imply that offshoring is unlikely to have a negative effect on unemployment incidence and duration.

To conclude, our findings suggest that the short-term effects of globalization on unemployment are either absent or ambiguous, and have a relatively small effect on unemployment compared to other worker and firm related predictors of unemployment and the probability of finding a new job. This implies that the short term transitional effects of globalization are unlikely to be important.

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