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Are workers with multinational experience a determinant in startup success?

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Abstract

This paper examines whether former foreign MNE workers help domestic startup firms succeed. I find evidence consistent with the idea that, as founding workers, former MNE workers positively contribute to startup outcomes. However, this appears conditional on survival. Using an event study approach on Irish administrative data, I do not find evidence that the wages of workers present from startup increase after former MNE workers join domestic firms. Likewise, there is no differential increase in size for startups joined by former MNE workers and startups that were not yet joined by former MNE workers. The same is true when examining wage outcomes at the worker level, even distinguishing between directors and non-directors, high and low wage workers. Former MNE workers are the highest earners in startups, suggesting that they have a higher ability than their peers. Challenges in adapting to a much less specialised environment and better wage bargaining may partly explain why former MNE workers do not appear to help startup firms succeed any more than other workers without this experience.

Keywords: foreign direct investment, spillovers, labour mobility, linked employer-employee data, wages

JEL Codes: F16, F23, J3, J6; D24, F23, J31, J60

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1 Introduction

This paper examines whether hiring former foreign multinational enterprise (MNE) workers helps startup firms succeed. There is much interest in FDI, including in spillovers to domestic firms. This paper addresses whether the first former MNE worker joining a domestic startup firm affects the size of the startup and the workers presence in the startup's first year.

I analyse startup firms in Ireland in the period 2006-2019 using an event study methodology. I begin with firm-level analysis; examining mean wages for workers present from startup and the number of workers in each firm to establish whether there is an overall effect of former MNE workers joining on startup firms. I do not find a significant effect on average wages of workers present associated with former MNE workers joining domestic startups. I also do not find evidence of increased growth in firm size in firms that hire their first former MNE worker, relative to firms that have yet to do so. Analysing outcomes at the worker level, I also do not find an effect on workers' wages, even when distinguishing between directors, men, women and low and high wage workers.

Comparing eventually treated firms with those who are never treated, I find that firms that are eventually treated have higher survival probabilities, grow more on average and their founding workers enjoy higher wages. Successful firms are more likely to come to hire more workers and hence former MNE workers, as well as having increased wages for founding workers.

As a more restrictive step that is less affected by this factor, I compare startups by their share of former MNE workers in their first year of existence. I divide them into four groups: no former MNE workers in the first group, and assign the others into three other groups based on their relative percentage shares. Here I find that firms with founding workers who are former MNE workers do typically perform better than firms without. However, they also display a higher probability of exit, suggesting that this finding is conditional on survival.

It has been established that foreign MNEs are more productive than domestic firms and workers in foreign MNEs earn more than workers in domestic firms, suggesting that they are more productive than them [Balsvik, 2011, Poole, 2013] (see [Flaherty, 2022] also). Former MNE workers are also the highest earners in startups, suggesting that they have higher ability or skills than their peers (Section 2.3). This finding suggests that may be able to bring this with them to domestic firms and increase the productivity and wages of incumbent workers there.

I contribute to two different literatures. First, I contribute to the FDI spillovers literature. While this literature is large, it has given relatively little attention to the effect of MNEs on startups to date. One exception is Burke et al. [2008], who analyse the effect of FDI on survival of startups in the UK. They find that the presence of MNEs reduces the probability of startup survival in sectors with a high churn in the number of firms, while it increases the probability of startup survival in sectors that have a relatively low churn in firms. Startup firms tend to be small. Insofar as firm size can proxy for startups, using data from Romania, Lenaerts and Merlevede [2015] find that size is not important factor as to whether domestic firms benefit from FDI spillovers. Another article in this literature is Görg and Strobl [2002]. Using data for the Irish manufacturing sector from 1974 to 1995, they find that there is a positive effect of the presence of foreign MNEs on the entry of indigenous firms in the economy. Conversely, analysing firm entry and exit across Belgian manufacturing from 1990 to 1995, De Backer and Sleuwaegen [2003] find that the presence of foreign MNEs discourages entry and stimulate exit of domestic entrepreneurs. They argue that this is due to domestic entrepreneurs being crowded out through selection in product and labour markets. Nonetheless, they find that their results suggest that there could be long term structural positive effects of FDI on domestic entrepreneurship due to learning, demonstration, networking and linkage effects that may moderate or even reverse this crowding out effect.

Analysing this topic has been impeded by data availability. Most startups are micro firms (firms with ten or less workers) [Bento and Restuccia, 2021]. Non-administrative data sources often do not include micro firms or only partially do so, which can result in their omission [Eslava et al., 2019]. Response rates from micro firms can also be worse than from larger firms. I overcome this challenge using a worker-level administrative panel tracking the universe of formal workers by firm and year in the Irish economy over a fourteen year period.

I also contribute to the economic literature on startups. Startups are important in contributing to the dynamism in an economy due to their heterogeneity in characteristics and outcomes [Haltiwanger et al., 2016]. Startups tend to start small and scale up or go out of business, often referred to as up or out dynamics. Haltiwanger et al. [2016] find that startups account for 10% of firms and more than 20% of firm-level gross job creation in the US. Most startups exit within 10 years, with the median surviving firm remaining small. However, some startups grow and contribute substantially to job creation. Startups have greater potential for innovation, and have higher growth rates compared to older firms, controlling for their size [Ouimet and Zarutskie, 2014]. Startups are also more sensitive than older firms to economic shocks [Fort et al., 2013].

While we know quite a bit about the performance of startup firms (described above), we know less about why they succeed. Surveying case studies in the business literature, Eisenmann [2021] provides insights into this. Lack of industry expertise may cause startups to fail. While they may have a good product idea, founders may lack sufficient industry experience or the right industry network, making it difficult to get the most out of their suppliers and re-sellers. In this situation, former MNE workers with the right expertise may help startups succeed. Alternatively, hiring veteran staff can bring this knowledge but they may not be able to adjust to becoming a jack of-all-trades in a small firm after being used to the specialisation of big corporations. Former MNE workers may experience this challenge.

The fact that former MNE workers are paid better than their peers may compell startups to focus harder on pursuing growth in order to pay for them. Eisenmann [2021] lists too much focus on growth as another reason why startups fail. Growth is very attractive and boosts morale. However, it can be at the cost of consumer research and premature product launch. It may also exacerbate quality problems and reduce profit margins. For the same reason, startups may also be too quick to start selling their product. This can leave them vulnerable to having to adapt it too many times, and expend scarce resources to do so.

A further reason why we may not observe spillovers to startup firms is that former MNE workers' compensation may be commensurate to the overall economic benefit that they bring to the startup firm. Economic surpluses within a firm are often shared heterogeneously. Kline et al. [2019] find that higher earnings from patent induced surpluses are captured by the top half of the earnings distribution. Along with being better skilled, former MNE workers may be be better placed to bargain within the firm than other workers and be fully compensated for their contribution, including spillover effects.

I use an event study methodology to examine the effect of hiring the first former MNE worker on startups. Given the small size of startups, a former MNE worker joining the firm can potentially have a large influence on the work of their colleagues. The objective of the event study approach is to estimate the average effect of a treatment on an outcome by year relative to the first year in the period (year -10). This is done by comparing groups over time based on different evolutions in their exposure to treatment using regressions that control for group and time fixed effects. Goodman-Bacon [2021] and subsequent papers have shown that standard difference-in-difference (DID) estimation methods using staggered designs can result in coefficients that are contaminated by effects in other periods. I use the two-way Mundlak regression proposed by Wooldridge [2021] to overcome this challenge. Specifically, I compare workers and firm outcomes for treated and not yet treated firms by regressing the dependent variable (worker level wages, firm-level mean wages and firm size) on dummy variables for each treatment cohort (grouping each worker or firm by the calendar year in which the firm is treated) interacted by dummy variables for each year in the data, a set of year dummies and unit (worker or firm) fixed effects. Cohort dummies for the years 2006 and 2007 are omitted. I subsequently aggregate the coefficients from the outcome variables. For example, I combine the coefficients on cohort 2016 with year dummy 2007, cohort 2017 with year dummy 2008, and cohort 2018 with year dummy 2009 to estimate the coefficients for pre-treatment years.

Among the literature of applied econometrics papers that use event studies, Choi et al. [2021] is particularly related. They use a matched survey-administrative data on firms in the US over 15 years to examine the causal impact of losing a founding team member on startup performance. They match startups with a death shock (where a founder had died) with other firms with similar characteristics except for the death shock and apply a differences in difference regression to it. They find that the death of a founding worker has a persistent, large, negative and statistically significant effect on the size, productivity and survival of a startup. This effect is particularly strong for all founding teams and firms in business to business sectors.

To the best of my knowledge, event studies have not been used in the context of FDI spillovers so far. Similarly, there has been very little empirical analysis of FDI spillovers through worker mobility between firms. The approach among the existing papers to date is to regress the share of former MNE workers on incumbent workers' wages, with the intuition that the higher the share of former MNE workers, the greater the probability of incumbent workers coming into contact with the former MNE workers and learning from them. Balsvik [2011], Poole [2013], Flaherty [2022] and Haller et al. [2023] use this approach. The event study approach can provide more definitive evidence of causality through exploiting the variation in when startup firms hiring their first former MNE worker.

The remainder of the paper is structured as follows: Section 2 provides a description of the data sets used, data preparation and summary statistics. Section 3 describes the methodology. Section 4 presents the results. Section 5 concludes.

2 Data

2.1 Data sources

My dataset is combined from three sources. My main data source is a worker-level administrative panel tracking the universe of formal workers in the Irish economy from the years 2005 to 2019. This provides me with the number of formal workers and their wages from the *SPP35* dataset from 2012 to 2018 and from the *PMOD* (**P**AYE **Mod**ernisation) dataset thereafter. This administrative dataset is based on tax records filed by employers through an income tax form called P35 on behalf of their workers to the Irish Revenue Commissioners (tax office). From 2019 onwards, the P35 dataset was replaced by the PMOD dataset, based on a real-time tax reporting system that replaced the annual P35 form. PMOD contains all of the variables available in the SPP35 and is comparable. Wages are defined as monthly real wages in euro (including benefits in kind and pension contributions). They are deflated using the Consumer Price Index. Unfortunately I do not have any other additional worker characteristics, such as years of school, measures of ability or hours worked. However, to the extent to which these do not change over time, these are included in workers' fixed effects.

This data is combined with worker characteristics from the Irish Department of Social Protection's *Client Record System* using a unique worker identifier. This additional data provides information on the number of weeks per firm and year that a worker has worked that are liable for social insurance contributions, and the following social welfare categories; pensioner, director or employee.[1]

I combine this data with firm characteristics from the Irish Central Statistics Office's (CSO) Business Register. The CSO Business Register covers all firms in the Irish economy and is based on data collected by the Irish Companies Registration Office. All firms in

[1]Some workers are categorised as being "employed" by pension firms, but are in fact pensioners receiving their pensions as income. These are what I mean by pensioners. I drop these workers as they are not really workers. Directors are workers categorised as company directors. Employees are workers that are not in these two categories.

Ireland must register with the Companies Registration Office and file an annual return with them. Firms that are incorporated outside Ireland and establish a subsidiary within Ireland must also register an Irish firm with the Companies Registration Office. I obtain data on whether firms are foreign multi-national enterprises (MNEs) from the Business Register and match it at the firm level with the Census of Industrial Production, using a unique firm identifier. Foreign MNEs are defined as companies that are a subsidiary of a parent firm abroad with an ownership stake of more than 50%. A full variable description is available in the Appendix (Section 6.1).

2.2 Data preparation

The worker-level dataset contains a separate entry for every registered employment position in Ireland in each year from 2006 to 2019.[2] I isolate workers based on their main social welfare category. Some workers are in one or all of the following categories; pensioner, director or employee. I assign workers to the category in which they have the most weeks of employment per year that are liable for social insurance contributions. Where they have 52 of each, I classify them as an employee. If they have 52 weeks as both a pensioner and a director, I classify them as a pensioner. I drop workers classified as pensioners.[3] I also exclude workers over 60 and workers under 25.

I first isolate market firms by excluding household employers and international/external government employers (NACE rev. 2 letters T and U), and workers in the public sector or similar (NACE letters O, P and Q). These steps leave me with 21 million worker-year observations in market firms over 10 years from 3.4 million unique workers in 301,140 unique firms. As I am interested in spillovers to domestic firms, I exclude subsidiaries foreign multinational firms from the analysis. This leaves me with 15.3 million worker-year

[2] I have data from 2005 to 2021 but the year 2006 is the first year in my regression sample as I do not have information on previous firm experience for workers in 2005. I exclude 2020 and 2021 from the analysis due to exceptional pandemic-related economic conditions in those years.

[3] Some workers are categorised as being "employed" by pension firms, but are in fact pensioners receiving their pensions as income. I drop these workers as they are not really workers.

observations from 2.9 million unique workers in 296,211 unique firms.

Next, I keep only startups. Following Haltiwanger et al. [2013], I define a startup as a firm that is 10 years old or younger. I am concerned about mistakenly classifying firms that have been newly created due to mergers, acquisitions or other corporate restructuring. Therefore I exclude firms with more than 15 workers in their first year. I also exclude firms that start with 10 workers or more and have 80% of their initial workers from the same firm or where their initial workers made up 80% or more of the previous firm's employees (e.g. 12 of 15 workers). This reduces the number of worker-year observations to 6.6 million. At this point, there are now 1.9 million unique workers in 238,069 unique startup firms.

I also exclude startups that existed before 2006 so that I can observe the first former MNE worker to join these startups, reducing the number of worker-year observations to 2.5 million. I drop startups with founding workers who are former MNE workers (these firms are known as always-treated in the literature). This leaves me with 1.6 million worker-year observations.

Finally, I drop all workers in firms except for founding workers. This results in a dataset of 662,211 worker-years; 212,995 unique workers in 116,982 unique startup firms.

Table 4 in the Appendix displays more detail on the data preparation process.

2.3 Worker outcomes before and after workers join startups

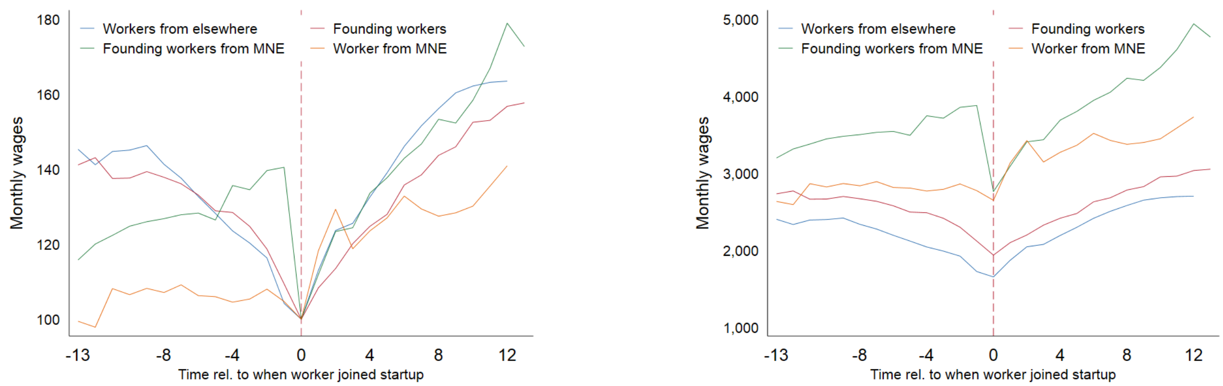
Former MNE workers are the highest earners in startups, suggesting that they have higher ability or skills than their peers, and thus may have more to bring to the firm [Balsvik, 2011, Poole, 2013] (see Flaherty [2022] and [Haller et al., 2023] also). Figure 1 shows mean worker wages before and after joining startup firms (defined by their group within those startups). The ranking of mean wages by worker category is the same both before and after joining domestic firms. Founding workers from foreign MNEs are highest paid, followed by workers who join later from foreign MNEs, followed in turn by founding workers who join from elsewhere and workers who join later from elsewhere.

Comparing mean wages by category in the year before joining, founding workers from MNEs earn the highest (3,871 euro per month). Workers who join later from foreign MNEs earn 2,802 euro per month. Founding workers who join from elsewhere earn the third largest amount (2,117 euro), while workers who join later from elsewhere earn the least (2,054 euro).

Examining this result using a level indexed to 100 in the joining year (Figure 1), all groups of workers joining startups take a pay cut relative to the year before joining. Founding workers from foreign MNEs take the steepest pay cut to join startups (-12%) but subsequently see the joint largest wage increases afterwards (48% four years on). Workers from MNEs who join later have the lowest reduction in wages (-4% in the year before) but also see the lowest increases in their wages afterwards (39% four years on). Both groups of workers joining from elsewhere have similar wage trajectories before and after (a cut of 11% followed by a 21% increase for founding workers from elsewhere, and a 11% cut followed by an increase of 16% for joiners from elsewhere). This locates their outcomes largely below those for founding workers from MNEs and above workers from MNEs who are not founding workers. While the wage ranking of the three groups is clear and likely associated with their relative productivity, it is difficult to distinguish which of them gain the most from joining startup firms.

2.4 Summary statistics: Startups in the economy

Table 1 shows startup firms in the economy relative to market firms in the economy overall (data corresponds to Stage 2 in Table 4 in the Appendix). In a given year, there are between 113 and 135 thousand market firms in in the economy. Startups make up between approximately half and two thirds of these firms. However, startups are typically only around a third of the size of the average market firm. This means that, of the 1.3-1.8 million workers in the economy annually, only between a seventh and a fifth are employed in startup firms.



(a) Index set to 100 where time = 0

(b) euro

Figure 1: Worker outcomes before and after joining startups

Notes: This figure shows mean worker wages (defined by group in startup firm) before and after joining startup firms. Ordering of mean wages by worker category is the same both before and after joining domestic firms. Source: Own calculations based on CSO data described in Section 2.2.

Figure 10 in the Appendix shows workers in startups, workers in all firms and startups and the share of workers in startups by sector. Startup firms are found in all sectors of the economy. The number of startups in a sector is generally correlated with the number of firms in that sector. The same can be said for the number of startup workers in a sector. There are also higher shares of startups in services sectors than in manufacturing.

2.5 Firms and workers by treatment status

Firms are defined as treated when the first former MNE worker joins the firm. Table 2 compares mean firm characteristics of startups used in my analysis (data corresponds to Stage 8 in Table 4) by whether they are treated, not yet treated or never treated. Always treated are excluded from this table. It compares treated firms in their first year of treatment to not yet treated firms in their pre-treatment year and never treated firms in their final year observed. Aged 2.8 years, the mean treated firm is a year older than the mean not yet treated firm (1.8), and slightly older than never treated (2.5). The mean treated firm has 6.8 workers; three workers more than the mean not yet treated firm (3.7) and four workers

Table 1: Market firms and startups by year

	Market firms	Share startups	Startup relative size	Workers market firms	Share workers in startups
2006	121,668	0.57	0.29	1,567,037	0.16
2007	129,358	0.58	0.30	1,657,972	0.17
2008	130,969	0.56	0.31	1,634,972	0.17
2009	121,540	0.53	0.31	1,450,196	0.16
2010	112,769	0.50	0.31	1,347,028	0.16
2011	113,520	0.49	0.32	1,335,553	0.16
2012	112,800	0.49	0.33	1,334,611	0.16
2013	113,566	0.49	0.34	1,363,014	0.16
2014	116,697	0.49	0.35	1,418,208	0.17
2015	120,227	0.49	0.35	1,485,079	0.17
2016	125,138	0.50	0.36	1,563,089	0.18
2017	119,222	0.48	0.39	1,596,713	0.19
2018	123,454	0.49	0.39	1,665,864	0.19
2019	135,326	0.53	0.37	1,770,206	0.20

Notes: Startups are defined as firms that are 10 years old or younger with less than 15 workers in their first year. Also excluded are firms that start with 10 workers or more and have 80% of their initial from the same previous firm or where firms' initial workers made up 80% or more of a previous firm's employees. Startup relative size is defined as the mean size of startups divided by the mean size of market firms. Share workers in startups is defined as the number of workers in startups divided by the number of workers in market firms.

Table 2: Firm characteristics by type

Variable	Treated	Not yet treated	Never treated
Firm age	2.84	1.78	2.56
N workers	6.82	3.70	1.97
Share female	0.41	0.40	0.34
Mean wage	1,976	2,093	2,013

Notes: This table compares treated firms in the first year of treatment to not-yet-treated firms in pre-treatment year and final year observed for never-treated firms. The firms here correspond to those present in the baseline analysis (Section 2.1). Source: Own calculations based on the administrative data described in Section 2.1.

more than the never treated firm (2). The mean treated firm's share of female workers is 41%; approximately the same as not yet treated firms (40%) and never treated (3.4%). Incumbent founding workers in treated firms are paid approximately the same as those in not yet treated firms and a little higher than those in never treated firms (mean monthly wages are 1,976, 2,093 and 2013 euro respectively).

Similarly, Table 3 shows the mean characteristics of incumbent founding workers (workers who joined the startup in its first year of existence) by the same set of firm types. This compares the means of founding workers in their first year of treatment to the equivalent in not yet treated firms in their pre-treatment year and never treated firms in the final year that they are observed. The mean founding worker is 38% likely to be female in treated and not yet treated firms, but only 33% likely in never treated firms. Founding workers are slightly less likely to be non-Irish in treated firms (22% versus 25% and 25% in not yet and never treated firms respectively). Aged 39 on average, founder workers are older in treated firms than in not yet treated (36) and never treated firms (38). Interestingly, the mean founding worker in treated firms has 10 colleagues compared to just four in not yet treated and two in never treated firms.

Founding workers in treated firms have slightly higher wages in the final year of their previous firm (2,894 euro) relative to workers in not yet treated (2,155 euro) and never treated firms (2,169 euro). However, workers in never treated firms come from the largest

Table 3: Founder worker characteristics by type

Variable	Treated	Not yet treated	Never treated
Female	0.38	0.38	0.33
Non-Irish	0.22	0.25	0.25
Age	39.47	35.54	38.29
Mean wage	2,894	2,155	2,170
N workers	11.13	5.18	3.15
Mean wage in prev. firm	2,549	2,326	2,393
Old firm size	296	369	386

Notes: This table compares founder worker characteristics in treated firms in the first year of treatment to founder worker characteristics in not-yet-treated firms in pre-treatment year. Except for the never-treated firms, firms here correspond to those present in the baseline analysis (Section 2.1). Never-treated firms are not compared in a staggared event study approach following Wooldridge (2021). They are only shown here for comparison purposes. Worker wages in previous firm to their wages in the year before they left. Old firm size refers the number of workers in the worker's previous firm in the year before they left. Source: Own calculations based on the administrative data described in Section 2.1.

firms (386 workers) compared to 368 in not yet treated firms and 296 in treated firms.

Figure 2 shows the 154,091 startups founded between 2006 and 2019 grouped by year of treatment relative to the year the firm was set up. The bars of this chart are truncated at 10,000. The largest category of firms were those that were never treated (93.9 thousand, or 61%). The second largest category were treated in the first year of the firm's existence 36.7 thousand (24%). These firms – known as always treated – are omitted from the event study part of the analysis. The next highest category (9 thousand or 6%) joined in the second year of firms' existence. The number of firms treated for the first time declines progressively with each year.

Figure 11 in the Appendix illustrates how initially there are between approximately 55 thousand and 75 thousand market firms annually in the economy in the period 2006 and 2019. These contain between 210 and 135 thousand workers (Figure 11b). Dropping firms in existence before 2006 leads to the patten changing to a steady increase over the period, converging with the total number of startups in 2016.

Figure 3 plots startup mean monthly income for founding workers by different time

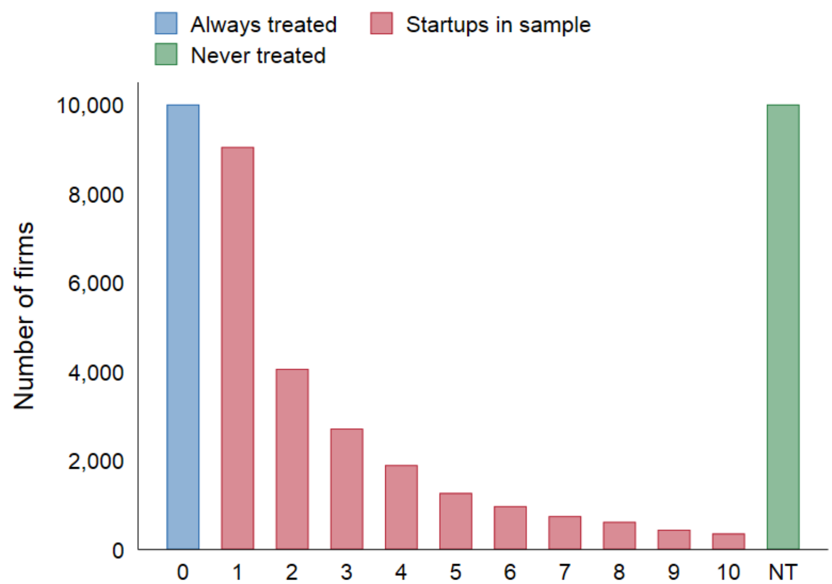


Figure 2: Startups from 2006-2009: First former MNE worker by firm age

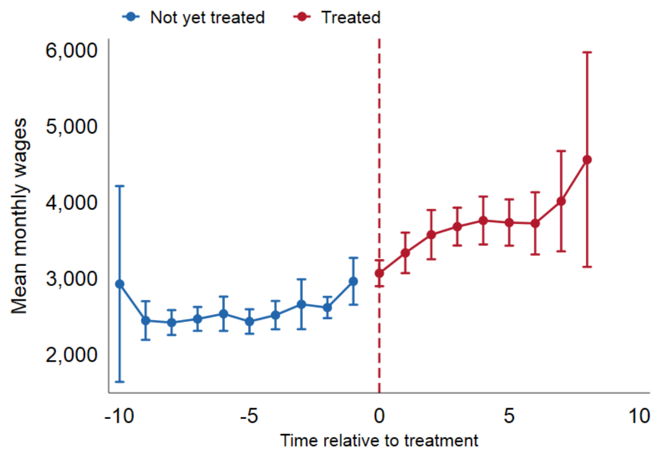
Notes: This figure shows the number of startup firms by the age at which the first former MNE worker joined the firm. Firms that had a former MNE worker as a founding worker are absent as they are omitted from the analysis. The bars are truncated at 10,000. The number of always-treated and never treated firms is 36,754 and 93,965 respectively. 'NT' refers to firms that are never treated. Source: Own calculations based on the administrative data described in Section 2.2.

measures.

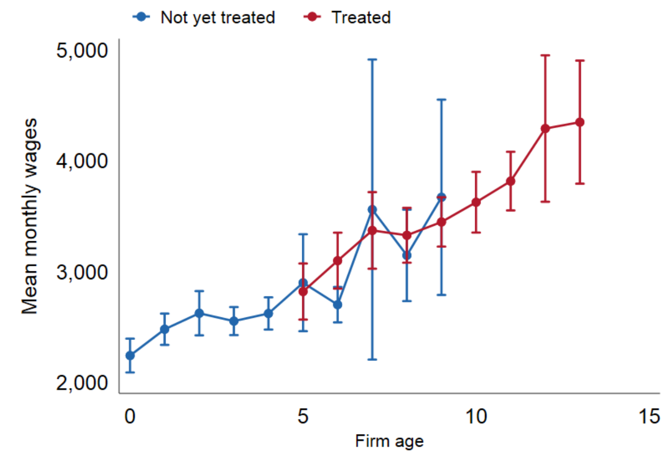
Figure 3a shows mean monthly income of founding workers by relative year. Here the difference in between treated and not yet treated is on-trend. There is no jump at the point in treatment.

Similarly, there is no difference between treated and not yet treated when comparing by firm age (Figure 3b). We can say that firms' founding workers ages grow, but in the raw data there is no jump associated with the first former MEN worker joining, or increased growth in wages after treatment. The story for firm size is different. This refers to the number of works in the firm, so treatment itself will affect firm size mechanically. Figure 3c shows that firm size jumps in the event of treatment.

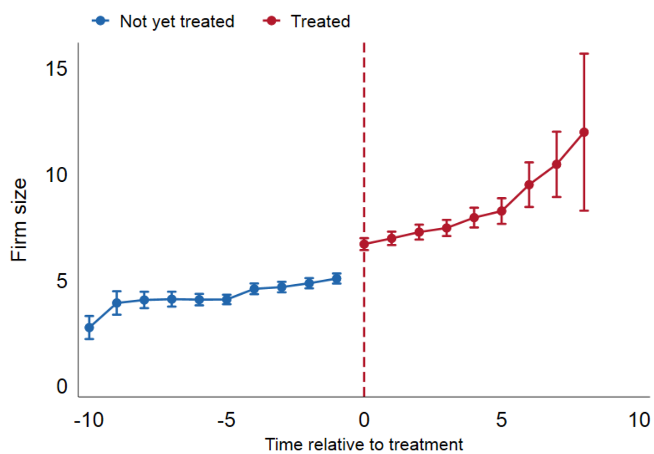
Figure 3d shows that treated firms are larger than not treated ones, even those of the same age. However, like what we saw with the wages, employment does not grow any faster, implying that firms hire former MNE workers as part of hiring but these former MNE workers do not cause the firm to grow any faster in the period considered (up to nine years for never treated firms). This indicates a once off jump that simply coincides with former MNE workers joining, suggesting firms that hire more are more likely to hire their first former MNE workers.



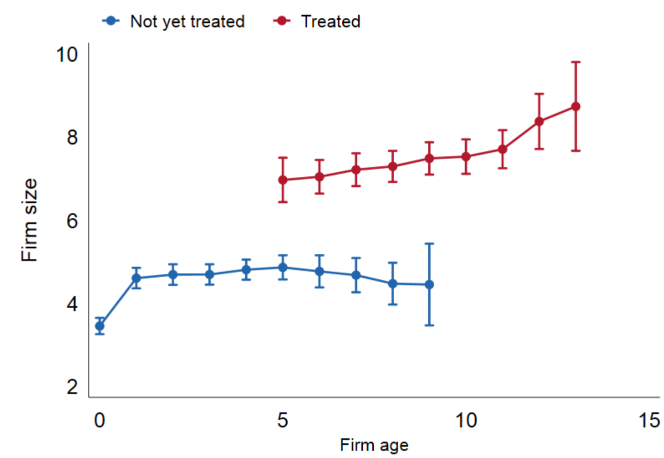
(a) Time relative to treatment



(b) Firm age



(c) Time relative to treatment



(d) Firm age

Figure 3: Startup outcomes by different time measures

Notes: This figure shows startup size (n workers) and mean monthly income for founding workers by treated and not yet treated and different time measures by treated and not yet treated and different time measures. Source: Own calculations based on CSO data described in Section 2.2.

2.6 Eventually treated and never treated

Figure 15a shows firm survival by eventually treated (not including those always treated) and never treated. Firms that are never treated are much less likely to survive in their first year. Aged 2, only 40% of these firms still exist, and only 20% still exist by age 4. Firms that are eventually treated are much more likely to survive: 90% aged 2 and 60% aged 4. Aged 10, 20% of ever treated firms still survive, while only 7% of never treated do so. Figure 15b shows that most firms are never treated but by age 10, they are approximately the same in number.

Figure 15c shows firm size by eventually treated and never treated. Eventually treated are on wages double in size in first year and triple in size by age 10. Never treated increase only marginally. Figure 15d shows that eventually treated are always larger than never treated, almost 5 times those aged 10. Figures 15e and 15f shows further wage growth faster for eventually treated firms, although average wages start from approximately the same level aged 0. By age 10, founder wages are considerably larger.

From this analysis, it is evident that causality and eventually treated are inter-related. Eventually treated firms are larger and grow more, and have higher founder wage growth. However, eventually treated firms are more likely to hire and thus more likely to hire former MNE workers, and firms with greater employment growth are more likely to have higher founder wage growth. Eventually treated have higher numbers of workers from the beginning, but are much less numerous and have approximately the same wages.

2.7 Firms with former MNE workers as founders

One feature of the event study analysis is that always treated firms are not examined. In order to provide some evidence on these, I also compare outcomes of always treated firms to firms that have no former MNE workers in their first year. I define these workers as founding workers. A founding worker is a worker who is there from the first year of the establishment of the firm. The intuition for using this definition is that such workers are likely to be part of a core team that has been critical in the establishment of the firm from the beginning.

Figure 11a (Appendix) shows the distribution of firms by share of former MNE workers in their first year. I group these workers into four brackets. Group 1 refers to all 131,101 firms that have no former MNE workers in their first year while the remaining groups are evenly split by percentile into three groups by share of former MNE workers (13,144 firms in each group). This figure shows the distribution of startups firms by share. Most firms have no former MNE workers as a founder worker. Group 4 contains firms which solely have former MNE workers as founders (this typically consists of just one worker). The remaining groups are split at 41%. Figure 11b shows how large shares of workers at 50%, 33% and 66%. This approach is defined more formally in Section 3.2.

Figure 16 (Appendix) shows startup outcomes grouped by the share of former MNE workers in their first year in indices relative to the first year and in absolute numbers. The first group has no former MNE workers. Group 2 covers the bottom tercile of startups with former MNE workers in their founding year, Group 3 covers the middle tercile and Group 4 covers the top tercile.

Figure 16a shows that firm survival is moderately lower from firms with high shares (5% in year 10 for Group 4, versus 10% for Group 1, those with no former MNE workers). Figure 16b shows survival based on number of firms. Typically startups do not include any former MNE workers in their first year. There were 131 thousand firms in Group 1 in their first year compared to a total of 53 thousand for the other groups combined.

Figure 16c shows that firm size growth (in number of workers) is much higher for firms with higher shares of former MNE workers in first year. By year 10, firms with exposure in the top tercile compared to Group 1 (those with no former MNE workers in startup), just under 1.5 times their original wage in year 10. Figure 16d shows mean firm size in number of workers by group. Firms with no former MNE workers start with two workers, compared to one for firms in the 66-100% tercile. Firms in Group 2 have an average of six at the beginning. The largest firms grow the least and the smallest firms grow the most.

Figure 16e shows a more mixed picture for growth in founder wages. Founder wage growth is only slightly higher for firms in the top group compared to those with no former MNE workers. Those in the top group had 1.54 times their original wages in the founding years , compared to just under 1.48 for those in the lowest group. Figure 16f shows mean monthly founder wage outcomes in euros. In year 10, monthly pay is 3,322 euros for Group 4, compared to 1,998 euros for Group 1. Group 2, the group with the highest wage growth, had the lowest initial wage (1793 euros). Group 4 workers earn 5,108 euros in year 10, relative to 2,963 euros for Group 1.

Taken together, Figure 16 shows that startups with former MNE workers are less likely to survive, with there are much fewer of them in each age group. Such firms also do not grow as much. However, with the exception of firms in Group 4, they are consistently larger. Founder wages grow faster in firms with former MNE founders and are also better paid in absolute terms (except form Group 2 in the first year).

These charts suggest that there is heterogeneity of across these groups in the initial year as well as in group outcomes. Later, I use regressions to control for this initial heterogeneity.

3 Methodology

3.1 Event study framework

I take two approaches to examine the effect of former MNE workers on startups. The first is to evaluate the effect of former MNE workers joining startups using a staggered event study approach following Wooldridge [2021] which exploits the variation in the timing of when the first former MNE worker joins different startup firms. I also compare treated startups to startups that do not have a former MNE worker in the treatment period. New firms tend to be small, where the majority of or all co-workers are likely to be exposed to each other, meaning that the influence of a former MNE worker may lead to better firm performance. This in turn may be measured in increased mean founding worker wages and firm size.

The standard Two-Way Fixed Effects (TWFE) difference in differences (DID) design is as follows:

$$y_{it} = \alpha_i + \lambda_t + \beta^{TWFE} d_{it} + \varepsilon_{it} \tag{1}$$

where y_{it} is an outcome for startup i in year t, α_i is the startup firm fixed effect, λ_t is a set of calendar time fixed effects, d_{it} is a variable interacting the period post treatment for the firms that are treated, β^{TWFE} captures the average treatment effect on the treated (ATT) and ε_{it} is the error term.

This approach can be staggered, where the time t is in relative years. The event study is an extended version of the DID approach. Equation 1 can be extended into an event study as follows:

$$y_{it} = \alpha_i + \sum_{k=-5}^{5} \lambda_k d[k]_{it} + \sum_{k=t}^{T} \delta_k d[k]_{it} \times TREAT_i + \tau_{ji} + \varepsilon_{it} \tag{2}$$

where y_{it} is an outcome for startup i in year t, $d[k]$ are a series of relative year dummies before and after the former MNE worker joins, $TREAT_i$ is the treatment dummy equal to one when the first former MNE worker joins, α_i is a firm fixed effect, τ_{ji} is an industry by year fixed effect, δ_k are the coefficients of interest (change in outcome each year for treated firms relative to the control group), and ε_{it} is the error term. In this standard approach, the reference period $k = -1$ is excluded.

The standard TWFE regression (Equation 1), where treatment is staggered, assumes homogeneous treatment effects by cohort (i.e. across timing of treatment by calendar time). However, recent advances in the econometric literature show that when treatment is staggered and the treatment effects are heterogeneous by treatment cohort, the estimated coefficients will be biased [Goodman-Bacon, 2021]. The biased TWFE estimate comes from the variance weighting of OLS and from using early treated units as control units for later treated units. The size of the treatment cohort and the length of the treatment also influence the estimated average treatment effects. The comparison year is the first period in the series, which is omitted.

Standard staggered event study estimates (Equation 2) are not as adversely affected by theses biases as the standard TWFE regression (Equation 1) since the length of exposure to treatment is taken into account explicitly. However, the lead and lag estimate may still be biased due to treatment effect heterogeneity and treatment effects from other relative time periods [Sayli et al., 2022].

Several econometric papers address these concerns. Wooldridge [2021] and Sun and Abraham [2021] add interaction terms for cohorts. Another approach is to transform the comparisons into a conventional two group-two period setting and staggering treatment effects [Callaway and Sant'Anna, 2021]. Other approaches include de Chaisemartin and d'Haultfoeuille [2020] and Borusyak et al. [2021].

I follow the estimation approach outlined by Wooldridge [2021]. Roth et al. [2023] suggests that Wooldridge is similar to four other methods. Specifically the theory behind Wooldridge is similar toBorusyak et al. [2021], Gardner [2022], Liu et al. [2024]. Results from empirical analysis using the different methods are also quite similar (Baker et al. [2022], Wooldridge [2023]).

The main advantage of Wooldridge [2021] is its transparency. One can split out the individual coefficients into their composition. Similarly, the Wooldridge methodology can be estimated without a package, allowing the analyst greater clarity about what is being estimated. The Wooldridge method is also more efficient than Callaway and Sant'Anna [2021] [Wooldridge, 2023].

The Wooldridge [2021] estimation equation is as follows:

$$E(y_{it}|d_{iq},....,d_{iT}) = \alpha + \lambda_q d_{iq} + ...\lambda_T d_{iT} + \sum_{s=2}^{T} \theta_s fs_t + \sum_{g=q}^{T} \sum_{s=g}^{T} \tau_{gs}(d_{ig} \cdot fs_t) \tag{3}$$

where y_{it} is the outcome for startup i in year t, d_{iq} is a set of dummies identifying each treated cohort and fs_t is a set of calendar year dummies. These results can then be aggregated over cohorts to provide coefficients by relative year (the approach taken here).

At the firm level, I use mean monthly wages for founding workers and firm size (the number of workers in the firm). I use firm age in the year prior to treatment and firm size in the year prior to treatment as controls where I have wages as the dependent variable. Where firm size is the dependent variable, I replace firm size with firm wages in the year prior to treatment as the control variable.

At the worker level, I use monthly wages wages as the dependent variable and control for worker age, a dummy variable for whether the worker is female and a dummy variable for whether the worker is non-Irish.

3.2 Analysis of outcomes based on share of founding workers from MNEs

I take a second approach to measure startup sectors. This approach borrows heavily from Elsner et al. [2024]. Here I make use of the always treated firms in my data that must necessarily be excluded from the event study and analyse the outcomes of these firms against other firms in the economy. These results cannot be taken as econometrically causal, but rather at least have the potential to be consistent with causality.

Here I first calculate share of founding workers from MNEs in the startup firm's first year. This is defined as follows:

$$FormerMNEshare_i = \frac{\text{n former MNE workers}_{it}}{\text{n workers}_{it}}. \tag{4}$$

where i refers to each firm and t refers to its first year of existence.

The goal here is to compare firm-level performance for firms with varying shares of former MNE workers as founding workers against those with none. Figure 11a (Appendix) shows the distribution of firms by share of former MNE workers in their first year. I group these workers into four brackets. I run the following regression separately for each firm age t from Age 1 to Age 10:

$$y_{it} = \beta_{1t} + \sum_{k=2}^{4} \beta_{kt} D_k + \boldsymbol{X_i'}\gamma + \varepsilon_{it}. \tag{5}$$

I regress outcome y_{it} of firm i in firm age t on three group dummies $D_2, \ldots, D_5$ in each year. Each dummy equals one if a firm's share of former MNE workers when they were aged 0 was in the respective group and zero otherwise. Firms with no former MNE workers make up the base category (Group 1). In some specifications, I also control for firm characteristics $\boldsymbol{X_i}$ (2 digit NACE rev. 2 industry and firm size in year 0) that are measured in the firm's first year. The error term ε_{it} summarizes all determinants of the outcome that are not included in the list of regressors.

My coefficients of interest are $\beta_{2t}, \ldots, \beta_{5t}$, the coefficients on the group dummies in each year of age. Each coefficient indicates the average difference in the outcome between startups in the respective group of the exposure distribution and firms in the bottom group. A statistically significant coefficient suggests that firms in group k have significantly different outcomes in age t compared to firms in the bottom group. I consider the following outcome variables: firm exit, firm size (n workers) and mean founder wages. The interpretation of the coefficients depends on the definition of the outcome. When the outcome is exit from the market (i.e. failure), the outcome equals one if a firm exits aged age t, and zero otherwise. In this case, the coefficient on the omitted category β_{1t} which is captured by the constant in the regression without controls measures the probability that a startup in Group 1 exited in period $t+1$ conditional on having survived until the firm is aged t. The coefficients on the dummy variables $\beta_{2t}, \ldots, \beta_{5t}$ measure the difference in this probability between the respective group and the bottom group (Group 1).

In the case of Δ firm size and Δ founder pay, I define y_{it} as the difference between the outcome in firm age t and in age 0. When this is the case, the omitted category β_{1t} (captured by the constant in the regressions without controls) measures the average difference in the outcome in the bottom group between firm age t and firm age 0. The coefficients on the dummy variables measure the change in outcome between firm year t and year 0 in Group k relative to the bottom group. A positive coefficient β_{kt} indicates that the average outcome in group k increased more (or decreased less) than the average outcome in the bottom group.

4 Results

4.1 Event study

4.1.1 Event study: firm-level outcomes

I begin with firm-level analysis using the event study method described in the previous section (Equation 3). I examine mean monthly wages for incumbent workers and the number of workers in each firm to establish whether there is an overall effect of former MNE workers on startup firms (Figure 4).

A central part of event study analysis is having parallel trends before treatment. In each of the event studies, we see parallel trends violated. Typically the coefficients become negative up to five years before treatment, followed by increasingly positive coefficients in the lead up to treatment. Coefficients are largest in the year of treatment before becoming no more statistically significantly different than zero. This indicates selection of workers in t-2 and t-1. Firms are either hiring former MNE workers as part of a wider growth increase or becoming more attractive as wages increase, or both.

Figure 4 shows firm level outcomes with controls. The values are are relative to $t - 10$. The results for mean wages of founding workers (Figure 4a) are negative in the years -9 to -5 and become positive and significant in the year before and of treatment. The subsequent years are not significant. These results suggest that former MNE workers joining is associated with a period of wage growth but do not cause it. The wage growth coefficient in the two significant years are each approximately 5%. This is not large in the context of firm wage growth in their first 10 years.

Figure 4b shows that firm size declines by 20% in several pre-treatment years, before increasing by 18% and 60% in the pre-treatment year and the year of treatment. Outcomes are not significantly different from zero in the subsequent years. Here the outcomes are also relatively small in the context of firm growth from a low base (e.g. from two to three workers). Therefore, an increase of 50% is not surprising in the context of treatment being a former MNE worker joining the firm.

A general pattern emerges. We observe wider confidence intervals further away from treatment based on fewer observation in this year (while we observe 14 periods in the charts, most treated firms are treated in the first two years prior to treatment, and will disappear out of the sample before 10 years. By virtue for the 10 year constraint on young firms and the constrains of the dataset, no firm is the sample for all 14 relative years.

Looking at the results by cohort, we see that most cohort-year interactions are not statistically significant, and only become so when aggregated. Table 5 shows the results for founding worker wages. Column (1) shows the results without controls. I only find significant pre-treatment coefficients in the year prior to treatment for cohorts 2008, 2009 and 2010. With one exception, there are no significant coefficients for the years prior to treatment. For the post treatment period, I find statistical significance for the 2009 cohort in the first seven post treatment periods. Cohort 2010 has statistical significance in the first two treatment periods. The 2016 cohort is statistical significant in in the year of treatment and less significant in the subsequent years. Except for these cohorts, the results are not significance at the 99% level. With controls (column 2), there are only two significant interaction terms; for one and two years after treatment for the 2017 cohort.

Table 6 shows the results for the log of firm size prior to aggregation. There are no statistically significant pre-treatment coefficients. However, there are significant post-treatment values. Cohorts 2008-2018 all have statistically significant coefficients on treatment. Cohort 2018 has statistically significant coefficients for one and two years post treatment also. There are more statistically significant values for analysis with controls. The 2008 cohort has one year of positive statistically significant pre-trends and 2017 has significant coefficients for all post treatment years.

4.2 Event study

4.2.1 Event study: worker-level outcomes

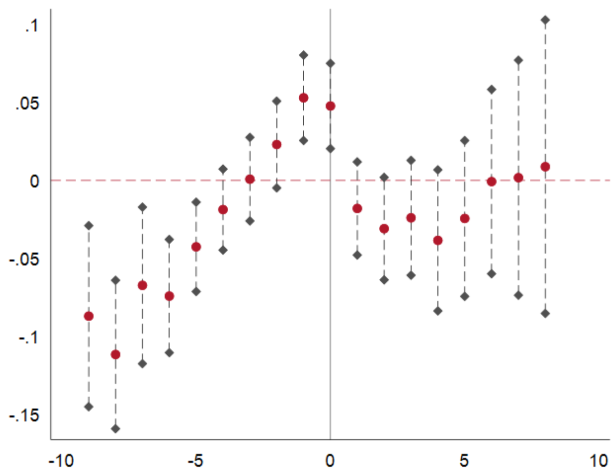
Next, I analyse outcomes at the worker level.[4] Figure 5a shows outcomes for founding worker wages. The only significant values are in the year prior to and of firms' treatment. Almost none of the results split by worker type at the worker level are statistically significant: wages of directors of startup firms, women, low and high wage workers (Figures 5, 6b, 7). One exception is for workers results for men (Figure 6a) . Here too wage growth is only positive in the year prior to and of treatment. This suggests that there is no causal effect of former foreign MNE workers joining. Where there are positive outcomes they occur during the firm's initial growth phase.

Column 1 of Table 7 shows the pre-aggregation results for founder worker wages. Following equation 3, years commencing with d refer to the year cohort, while years commencing with f refer to the treatment year. All cohorts except for 2011, 2017 and 2018 have statistical significance in the year of treatment (where calendar year equals treatment year). The coefficients tend to decline and become less significant in subsequent years.

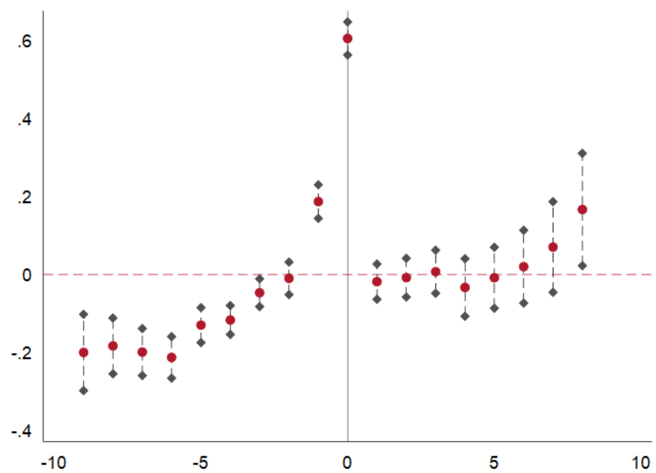
4.2.2 Robustness tests: alternative treatment definitions

Here I create alternative definitions of treatment. The first defines treatment as the presence of the first former MNE worker who is also a former manager (where manager is a worker

[4] All worker-level regressions use founding workers only (workers who were in the firm from the first year onwards).



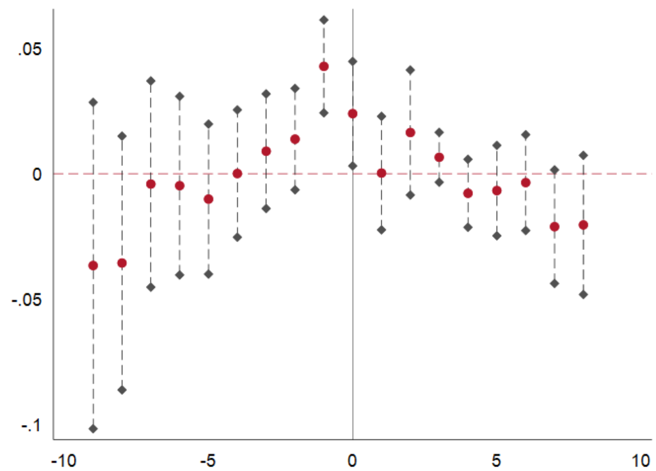
(a) Mean wages of founding workers



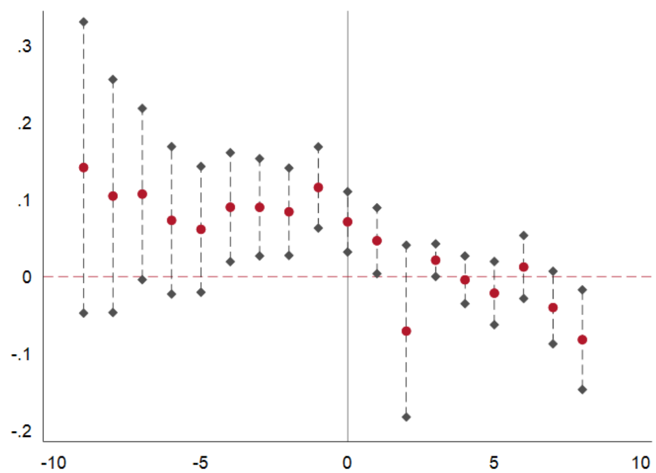
(b) Firm size

Figure 4: Firm-level analysis

Notes: This figure shows firm-level event study results from Equation (3). The outcome variables listed in the sub-captions are are regressed on time periods, the aggregated coefficients of which are shown in the graphs. Outcomes are relative to the first time period in the series (omitted). Confidence intervals are at the 95th percentile. Source: Own calculations based on CSO data described in Section 2.2.



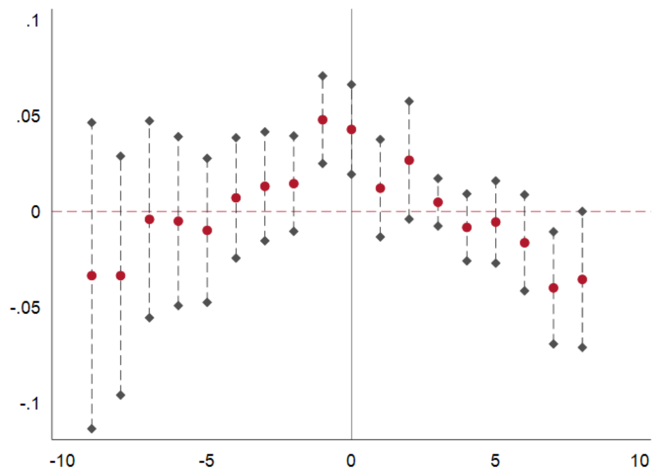
(a) All founding workers



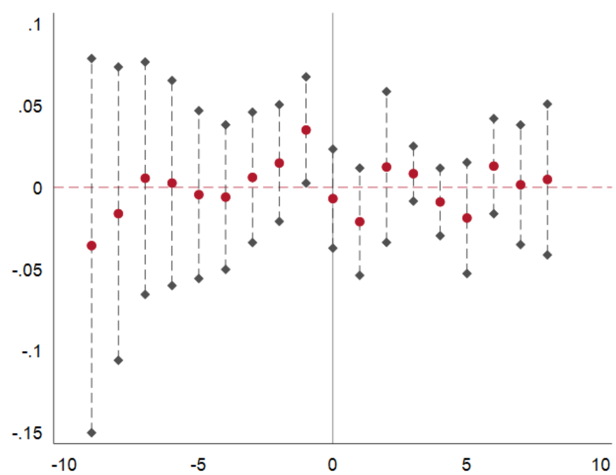
(b) Directors

Figure 5: All founding workers and directors

Notes: This figure shows firm-level event study results from Equation (3). The outcome variables listed in the sub-captions are are regressed on time periods, the aggregated coefficients of which are shown in the graphs. Outcomes are relative to the first time period in the series (omitted). Confidence intervals are at the 95th percentile. Source: Own calculations based on CSO data described in Section 2.2.



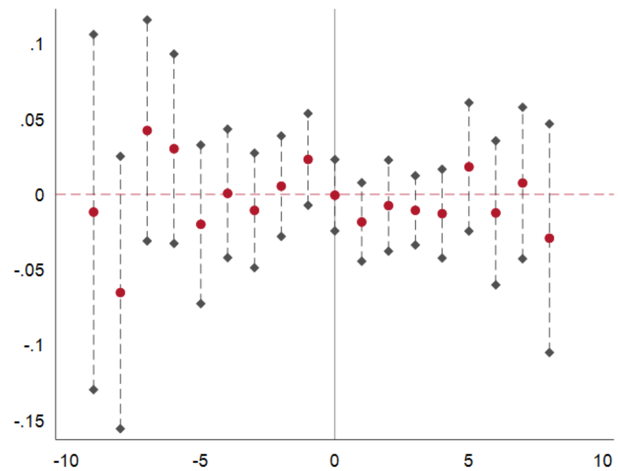
(a) Men



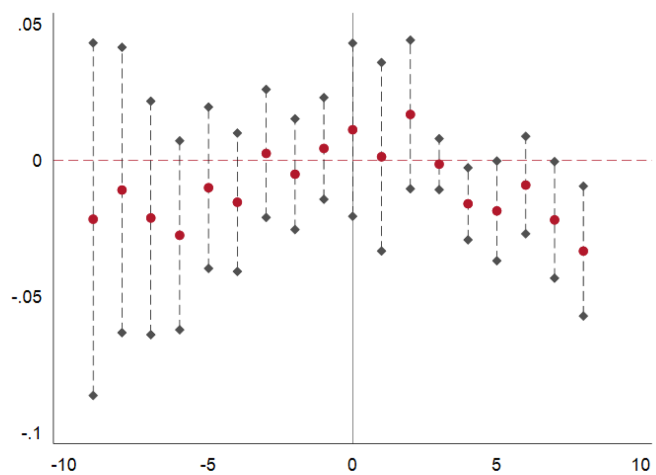
(b) Women

Figure 6: Men and women

Notes: This figure shows firm-level event study results from Equation (3). The outcome variables listed in the sub-captions are are regressed on time periods, the aggregated coefficients of which are shown in the graphs. Outcomes are relative to the first time period in the series (omitted). Confidence intervals are at the 95th percentile. Source: Own calculations based on CSO data described in Section 2.2.



(a) Low wage workers



(b) High wage workers

Figure 7: Low and high wage workers

Notes: This figure shows firm-level event study results from Equation (3). The outcome variables listed in the sub-captions are are regressed on time periods, the aggregated coefficients of which are shown in the graphs. Outcomes are relative to the first time period in the series (omitted). Confidence intervals are at the 95th percentile. Source: Own calculations based on CSO data described in Section 2.2.

in the top 25% of the income distribution of an MNE with more than 10 workers in the year they leave). The second defines treatment as the presence of the first former MNE worker who is also a current manager (where I define manager as a worker in the top 25% of the income distribution of the startup with more than 10 workers in the year they join). The same pattern of treatment occurring mostly in the earlier years persists in both alternative treatment definitions (Figure 12, Appendix).

The results for this are found in Figures 13 and 14 in the Appendix. Here too the coefficients are typically positive at the point of treatment and become non-significant and even negative when they move further away from treatment. We also observe the same pattern of higher growth rates for firm size than founding worker wages.

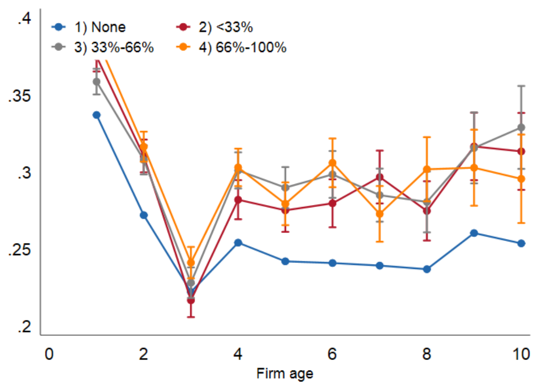
4.3 Firm outcomes by share of founding workers

Figure 8 shows regression outcomes of firm characteristics regressed on firm age, controlling for firms' size and industry (NACE 2.1 at the two digit level) in their first year.

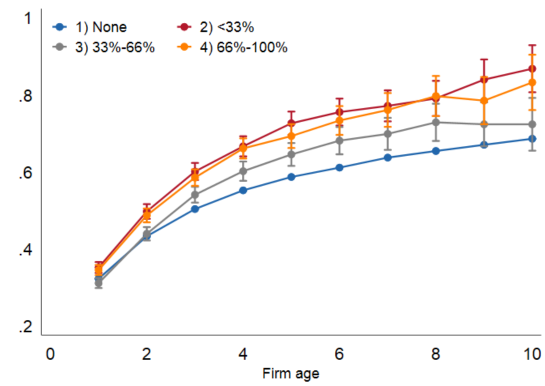
Figure 8 shows regression outcomes for startup firms grouped by share of former MNE workers in their first year. The first group has no former MNE workers. Group 2 covers the bottom tercile of startups with former MNE workers in their founding year, Group 3 covers the middle tercile and Group 4 covers the top tercile.

Figure 8a shows probability of exit is highest in year 1 of firms existence, for all groups. Firms in those with no former MNE workers have a lower probability of exit for all years (not statistically difference in year 3). The difference between the other groups is not statistically significant. Firms with former MNE workers are more likely to exit. Figure 8b shows that firm growth is highest for higher shares and lowers for no former MNE workers. Figure 8c shows that firm size levels are ambiguous. Most are not that statistically different from each other. Figure 8d shows that founding workers' wages are higher for all groups related to group 1.

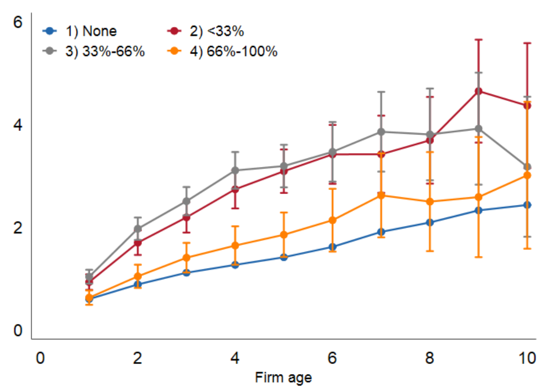
The outcomes here are similar to what we have observed in the summary statistics. In



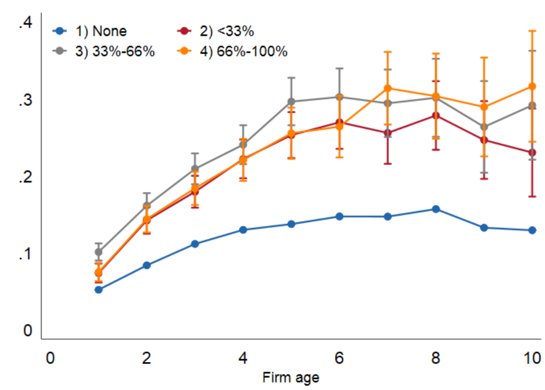
(a) Survival (probability of firm exit)



(b) Δ firm size



(c) Firm size



(d) Mean founding worker wages

Figure 8: Firm regression outcomes (including controls) grouped by shares of former MNE founding workers

Notes: This figure shows shows regression outcomes of firm characteristics regressed on firm age, controlling for firms' size and industry (NACE 2.1 at the two digit level) in their first year. They are grouped by share of former MNE workers defined in Section 2.7. Group 1 includes firms that have no former MNE workers in their first year of existence, while groups 2,3 and 4 are grouped by tercile of the remaining workers. Source: own calculations based on the administrative data described in Section 2.2.

summary, firms with former MNE workers as founders are more likely to exit in every year, suggesting that many are less suited to small firms after being in large corporations (Figure 8a). Firms with former MNE workers as founders grow faster (Figure 8b) and are typically larger (Figure 8c) while their founding workers wages increase faster. Tables 8, 9, 10 and 11 (Appendix) show these regression results with and without controls. These results indicate that, except in the case of exit, startups with former MNE workers perform better than their peers.

5 Conclusion

Using an event study approach on Irish administrative data, I examine whether the mean wages of founding worker increase when former MNE workers joining domestic firms. I do not find evidence of an effect. I also do not find evidence of increased growth in firm size in firms that hire their first former MNE worker, relative to firms that have yet to do so. Analysing outcomes at the worker level, I also do not find significant effects on workers' wages, even when distinguishing between directors, men, women and low and high wage workers.

Founding workers from MNEs earn the highest amount before and after joining startups, while workers who join later from foreign MNEs are the second highest earners. Founding workers who join from elsewhere are third, while workers who join later from elsewhere earn the least. MNEs are very different to startups. One possible explanation is that while former MNE workers are likely higher in ability than their peers, indicated by their higher wages, challenges in adapting to a much less specialised environment may be why former MNE workers joining may not help startup firms succeed any more than non-former MNE workers do so

Economic surpluses in firms are often shared heterogeneously. Another possible explanation is that former MNE workers keep the economic surplus that they bring to the firm through strong wage bargaining. This would be consistent with improved performance but would eliminate measured spillover effects. Comparing eventually treated firms with those who are never treated, I find that firms that are eventually treated have higher survival probabilities, grow more on average and their founding workers enjoy higher wages. However, these outcomes do not indicate causality. Successful firms are more likely to come to hire more workers and hence former MNE workers, as well as having increased wages for founding workers.

Finally, I compare startups' outcomes by their share of former MNE workers in their first year of existence. I group these workers into four brackets. The first group consists of firms with no former MNE workers. Th other groups are by tercile based on their relative shares of former MNE workers. Here I find that firms with founding workers who are former MNE workers do typically perform better than firms without them.

One exception is that firms with founders from MNEs are more likely to exit the market. This may mean that former MNE workers are less able to adapt to small firms after the specialisation of a large corporation. Another explanation is that former MNE workers are more prepared (or able) to fail early than founders without this experience.

In summary, this paper provides evidence that, as founding workers, former MNE workers positively contribute to startup outcomes. However, this is conditional on survival. Firms with former MNE workers are also more likely to fail. Furthermore, as joiners to startup forms, former MNE workers do not appear to be any more useful than workers without this experience.

Further research is needed to learn more about why startups with former MNE workers in their first year are more likely to fail. It may be no harm if a startup fails early if it is because the founders have come to the reasoned conclusion that cutting their losses early is for the best. However, there is a risk that former MNE workers are abandoning high potential startup because the more difficult early years just not as attractive as outside employment options, at the cost of greater innovation, and wealth and employment creation.

Policy must enable higher skilled workers to take the appropriate risks involved in starting up firms; allowing and encouraging them to stay in business for long enough to bring viable ideas to fruition. Fortunately, there is a great deal of policy measures that public authorities can use in this space. These include carefully tailored tax incentives (such as tax credits and capital allowances), welfare benefits and the availability of grants. They can also provide the appropriate startup hubs and business incubation centres, as well as backing bank loans and making strategic equity investments. Taking the appropriate actions here can increase economic dynamism through ensuring greater startup success.

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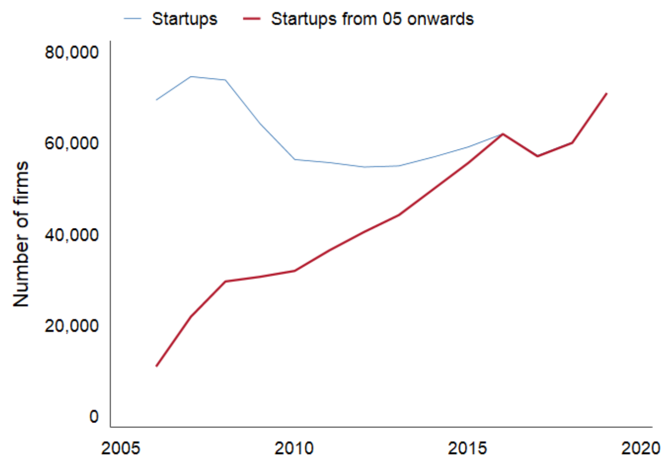
6 Appendix

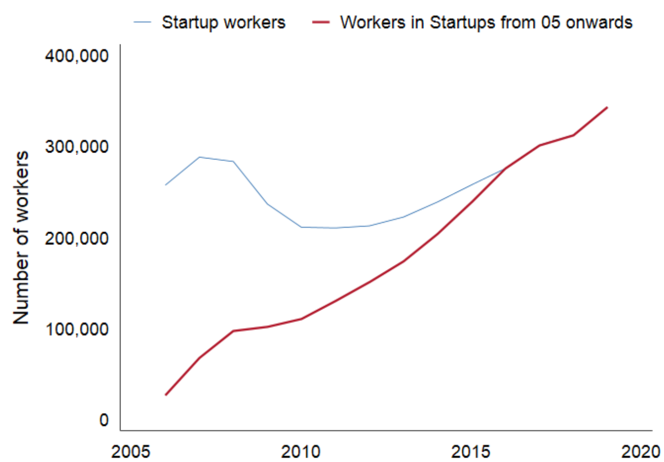
Table 4: Breakdown of firms in the economy

Stage	Worker-years	Workers	Firm-years	Firms
1	28,745,404	4,016,539	1,918,697	332,159
2	21,189,542	3,381,763	1,696,254	301,140
3	15,347,612	2,912,080	1,645,375	296,211
4	6,577,336	1,933,478	941,248	238,069
5	2,433,005	850,229	600,241	153,156
6	1,619,424	582,695	463,447	116,437
7	657,219	211,713	388,057	116,437

Notes: Stage 1: Population of workers. Stage 2: Exclude non-market firms. Stage 3: Exclude foreign MNEs. Stage 4: Keep startups. Stage 5: Exclude firms established before 2006. Stage 6: Exclude always-treated. Stage 7: Keep founding workers.



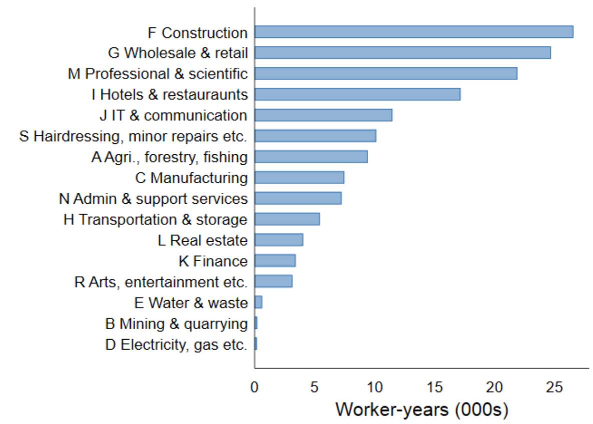
(a) Startups



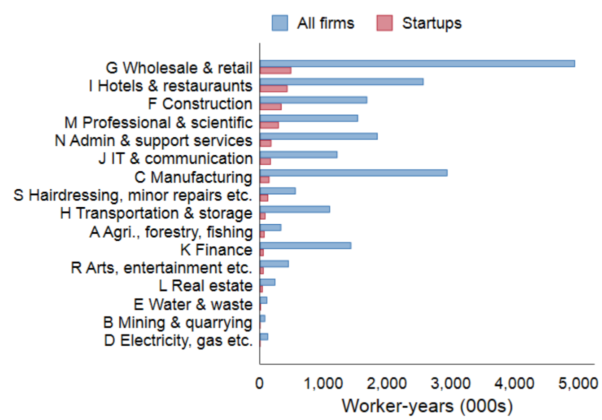
(b) Startup workers

Figure 9: All startups compared to those from 2006 onwards and those in estimation sample

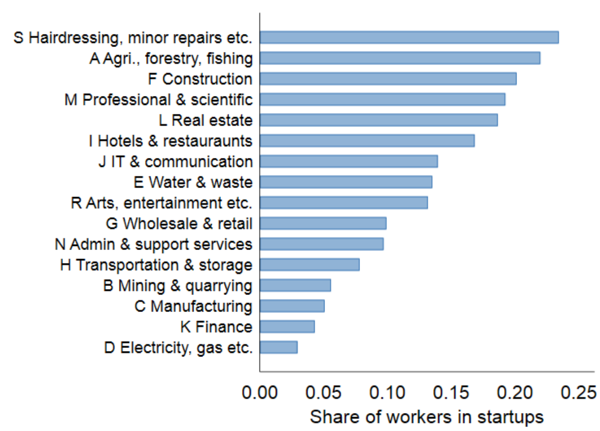
Notes: This figure show the number of firms and startups in the economy over time. It compares those in the economy overall to those found founded from 2006 onwards and those used in the estimation sample. Source: Own calculations based on CSO data described in Section 2.2.



(a) Workers in startups



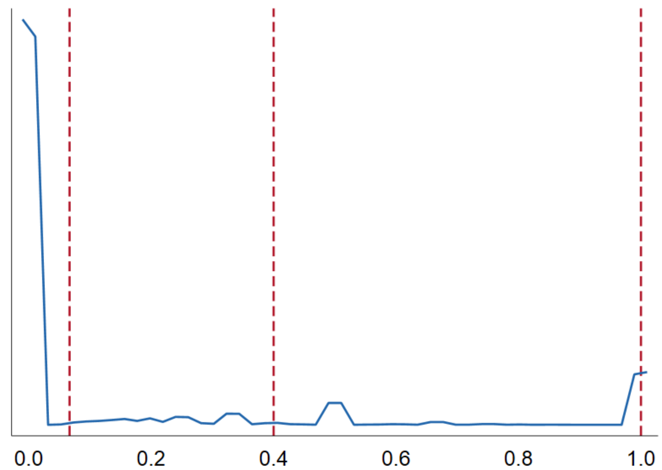
(b) Workers in all firms and startups



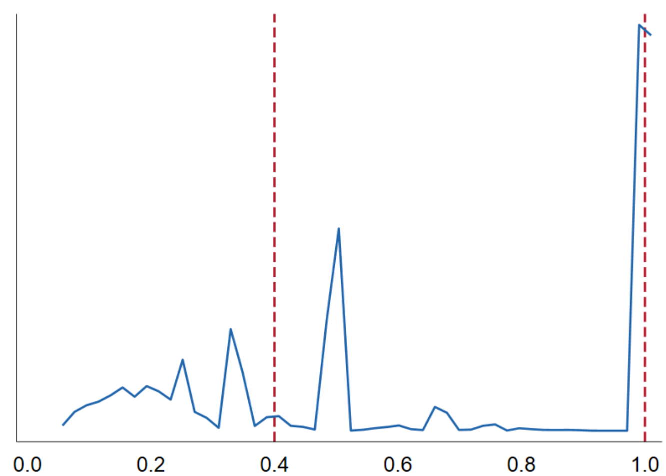
(c) Share of workers in startups

Figure 10: Workers in startups by sector

Notes: This figure shows workers in startups, workers in all firms and startups and the share of workers in startups by sector for all market firms in the economy. Startup firms are found across the economy. Workers in startups are found in particular in sectors with high numbers of workers overall. Workers in startups are also more likely to be found in services than manufacturing. Source: Own calculations based on CSO data described in Section 2.2.



(a) All firms



(b) Excluding firms in Group 1

Figure 11: Distribution of shares of founding workers formerly in MNEs

Table 5: Firm-level event study results before aggregation by relative time

Dependent variable:	(1)		(2)	
ln(mean founding worker monthly wages)	No controls		Controls	
d2008 × f2008	0.126	(0.037) ***	-0.066	(0.143)
d2008 × f2009	0.004	(0.042)	-0.205	(0.145)
d2008 × f2010	0.031	(0.046)	-0.209	(0.146)
d2008 × f2011	0.012	(0.048)	-0.254	(0.146) *
d2008 × f2012	0.048	(0.050)	-0.225	(0.146)
d2008 × f2013	0.013	(0.053)	-0.252	(0.147) *
d2008 × f2014	0.054	(0.057)	-0.175	(0.148)
d2008 × f2015	0.105	(0.058) *	-0.101	(0.150)
d2008 × f2016	0.123	(0.060) **	-0.049	(0.150)
d2008 × f2017	0.128	(0.071) *	0.002	(0.165)
d2008 × f2018	0.000	(.)	0.000	(.)
d2009 × f2009	0.019	(0.044)	0.084	(0.124)
d2009 × f2010	-0.061	(0.047)	-0.031	(0.125)
d2009 × f2011	-0.079	(0.049)	-0.054	(0.126)
d2009 × f2012	-0.077	(0.052)	-0.070	(0.127)
d2009 × f2013	-0.076	(0.054)	-0.067	(0.127)
d2009 × f2014	-0.087	(0.056)	-0.063	(0.126)
d2009 × f2015	-0.092	(0.056) *	-0.064	(0.129)
d2009 × f2016	-0.119	(0.057) **	-0.065	(0.128)
d2009 × f2017	-0.032	(0.059)	0.040	(0.129)
d2009 × f2018	-0.017	(0.071)	0.101	(0.188)
d2010 × f2010	0.226	(0.043) ***	0.182	(0.060) ***
d2010 × f2011	0.144	(0.044) ***	0.072	(0.059)

d2010 × f2012	0.110	(0.046)	**	0.046	(0.060)	
d2010 × f2013	0.108	(0.046)	**	0.051	(0.060)	
d2010 × f2014	0.099	(0.046)	**	0.035	(0.057)	
d2010 × f2015	0.062	(0.046)		0.005	(0.057)	
d2010 × f2016	0.108	(0.045)	**	0.048	(0.053)	
d2010 × f2017	0.039	(0.045)		-0.026	(0.050)	
d2010 × f2018	-0.033	(0.045)		-0.069	(0.061)	
d2011 × f2011	0.071	(0.038)	*	0.103	(0.044)	**
d2011 × f2012	0.041	(0.039)		0.040	(0.043)	
d2011 × f2013	0.042	(0.039)		0.030	(0.043)	
d2011 × f2014	0.072	(0.039)	*	0.070	(0.042)	*
d2011 × f2015	0.074	(0.037)	**	0.055	(0.040)	
d2011 × f2016	0.038	(0.037)		0.012	(0.038)	
d2011 × f2017	0.065	(0.036)	*	0.057	(0.037)	
d2011 × f2018	0.040	(0.035)		0.024	(0.038)	
d2012 × f2012	0.094	(0.036)	**	0.100	(0.039)	**
d2012 × f2013	0.029	(0.037)		0.030	(0.039)	
d2012 × f2014	-0.005	(0.036)		-0.016	(0.038)	
d2012 × f2015	0.010	(0.034)		0.010	(0.037)	
d2012 × f2016	0.014	(0.033)		0.010	(0.034)	
d2012 × f2017	0.001	(0.032)		-0.016	(0.033)	
d2012 × f2018	0.009	(0.030)		-0.007	(0.031)	
d2013 × f2013	0.082	(0.033)	**	0.080	(0.034)	**
d2013 × f2014	0.028	(0.032)		0.020	(0.033)	
d2013 × f2015	0.009	(0.031)		-0.000	(0.031)	
d2013 × f2016	0.011	(0.029)		0.004	(0.029)	
d2013 × f2017	0.010	(0.028)		-0.001	(0.028)	

d2013 × f2018	0.030	(0.026)	0.014	(0.025)
d2014 × f2014	0.085	(0.029) ***	0.108	(0.030) ***
d2014 × f2015	0.049	(0.027) *	0.053	(0.028) *
d2014 × f2016	0.031	(0.027)	0.026	(0.026)
d2014 × f2017	0.018	(0.025)	0.010	(0.024)
d2014 × f2018	-0.022	(0.022)	-0.026	(0.022)
d2015 × f2015	0.060	(0.025) **	0.063	(0.025) **
d2015 × f2016	0.008	(0.023)	0.004	(0.023)
d2015 × f2017	-0.002	(0.022)	-0.005	(0.021)
d2015 × f2018	0.004	(0.020)	-0.002	(0.020)
d2016 × f2016	0.080	(0.019) ***	0.039	(0.020) *
d2016 × f2017	0.018	(0.018)	-0.013	(0.018)
d2016 × f2018	0.026	(0.017)	-0.004	(0.016)
d2017 × f2017	0.010	(0.020)	0.046	(0.020) **
d2017 × f2018	-0.035	(0.018) **	0.008	(0.018)
d2018 × f2018	0.015	(0.014)	0.027	(0.020)
d2008 × f2007	0.089	(0.035) **	-0.009	(0.142)
d2009 × f2007	-0.079	(0.041) *	-0.051	(0.120)
d2009 × f2008	-0.051	(0.042)	0.021	(0.118)
d2010 × f2007	0.130	(0.044) ***	0.046	(0.075)
d2010 × f2008	0.088	(0.042) **	-0.008	(0.066)
d2010 × f2009	0.135	(0.044) ***	0.077	(0.066)
d2011 × f2007	-0.020	(0.043)	0.013	(0.069)
d2011 × f2008	0.060	(0.041)	0.073	(0.069)
d2011 × f2009	0.065	(0.045)	0.152	(0.082) *
d2011 × f2010	0.055	(0.038)	0.133	(0.049) ***
d2012 × f2007	0.042	(0.044)	0.036	(0.069)

d2012 × f2008	-0.008	(0.042)	-0.005	(0.064)
d2012 × f2009	-0.017	(0.040)	-0.018	(0.055)
d2012 × f2010	0.021	(0.037)	0.072	(0.047)
d2012 × f2011	0.081	(0.037) **	0.120	(0.042) ***
d2013 × f2007	-0.082	(0.044) *	-0.119	(0.069) *
d2013 × f2008	-0.011	(0.042)	-0.016	(0.057)
d2013 × f2009	0.059	(0.039)	0.048	(0.050)
d2013 × f2010	0.036	(0.038)	0.049	(0.045)
d2013 × f2011	0.019	(0.035)	0.063	(0.040)
d2013 × f2012	0.048	(0.034)	0.077	(0.036) **
Constant	7.455	(0.009) ***	7.240	(0.158) ***
N	381,226		103,828	
N firms	114,918		19,951	
Adj. R^2	0.055		0.111	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Firm-level event study results before aggregation by relative time

Dependent variable:	(1)		(2)	
ln(firm size)	No controls		Controls	
d2008 × f2008	0.605	(0.057) ***	1.110	(0.210) ***
d2008 × f2009	-0.173	(0.059) ***	0.247	(0.210)
d2008 × f2010	-0.156	(0.063) **	0.234	(0.212)
d2008 × f2011	-0.112	(0.065) *	0.227	(0.212)
d2008 × f2012	-0.065	(0.067)	0.265	(0.212)
d2008 × f2013	-0.053	(0.070)	0.277	(0.213)
d2008 × f2014	-0.082	(0.071)	0.270	(0.213)

d2008 × f2015	0.018	(0.072)	0.419	(0.213) **
d2008 × f2016	0.042	(0.075)	0.523	(0.214) **
d2008 × f2017	0.233	(0.079) ***	0.945	(0.227) ***
d2008 × f2018	0.000	(.)	0.000	(.)
d2009 × f2009	0.644	(0.060) ***	0.412	(0.207) **
d2009 × f2010	-0.053	(0.061)	-0.427	(0.207) **
d2009 × f2011	-0.053	(0.062)	-0.476	(0.207) **
d2009 × f2012	-0.039	(0.063)	-0.468	(0.207) **
d2009 × f2013	-0.031	(0.065)	-0.460	(0.207) **
d2009 × f2014	-0.006	(0.066)	-0.422	(0.208) **
d2009 × f2015	-0.021	(0.067)	-0.413	(0.208) **
d2009 × f2016	-0.041	(0.068)	-0.390	(0.208) *
d2009 × f2017	-0.025	(0.069)	-0.281	(0.210)
d2009 × f2018	-0.034	(0.075)	-0.535	(0.297) *
d2010 × f2010	0.709	(0.050) ***	0.874	(0.061) ***
d2010 × f2011	0.035	(0.048)	0.072	(0.058)
d2010 × f2012	0.038	(0.048)	0.065	(0.057)
d2010 × f2013	0.036	(0.048)	0.058	(0.057)
d2010 × f2014	0.057	(0.048)	0.070	(0.056)
d2010 × f2015	0.047	(0.047)	0.073	(0.054)
d2010 × f2016	0.051	(0.047)	0.064	(0.052)
d2010 × f2017	0.059	(0.046)	0.094	(0.051) *
d2010 × f2018	0.031	(0.045)	0.125	(0.062) **
d2011 × f2011	0.625	(0.045) ***	0.821	(0.053) ***
d2011 × f2012	-0.001	(0.043)	0.058	(0.048)
d2011 × f2013	0.006	(0.042)	0.051	(0.047)
d2011 × f2014	0.004	(0.041)	0.045	(0.045)

d2011 × f2015	0.007	(0.040)	0.034	(0.043)
d2011 × f2016	0.037	(0.038)	0.059	(0.040)
d2011 × f2017	-0.013	(0.036)	0.032	(0.039)
d2011 × f2018	-0.067	(0.035) *	-0.049	(0.040)
d2012 × f2012	0.553	(0.039) ***	0.682	(0.044) ***
d2012 × f2013	-0.048	(0.037)	-0.020	(0.041)
d2012 × f2014	-0.032	(0.036)	-0.014	(0.039)
d2012 × f2015	-0.024	(0.035)	-0.005	(0.038)
d2012 × f2016	-0.024	(0.034)	-0.002	(0.036)
d2012 × f2017	0.008	(0.031)	0.026	(0.034)
d2012 × f2018	0.034	(0.028)	0.039	(0.031)
d2013 × f2013	0.523	(0.033) ***	0.664	(0.037) ***
d2013 × f2014	-0.045	(0.031)	-0.026	(0.034)
d2013 × f2015	-0.003	(0.030)	0.008	(0.032)
d2013 × f2016	0.016	(0.028)	0.026	(0.030)
d2013 × f2017	0.003	(0.026)	0.019	(0.028)
d2013 × f2018	-0.005	(0.023)	-0.002	(0.025)
d2014 × f2014	0.578	(0.029) ***	0.702	(0.032) ***
d2014 × f2015	-0.001	(0.026)	0.015	(0.028)
d2014 × f2016	0.008	(0.025)	0.012	(0.027)
d2014 × f2017	0.023	(0.022)	0.019	(0.024)
d2014 × f2018	0.008	(0.019)	0.009	(0.022)
d2015 × f2015	0.529	(0.025) ***	0.625	(0.028) ***
d2015 × f2016	-0.015	(0.022)	-0.006	(0.024)
d2015 × f2017	-0.006	(0.020)	-0.001	(0.022)
d2015 × f2018	-0.004	(0.017)	0.002	(0.019)
d2016 × f2016	0.554	(0.021) ***	0.634	(0.024) ***

d2016 × f2017	0.020	(0.018)	0.000	(0.020)
d2016 × f2018	0.030	(0.016) *	0.011	(0.018)
d2017 × f2017	0.283	(0.021) ***	0.417	(0.024) ***
d2017 × f2018	-0.045	(0.016) ***	-0.004	(0.018)
d2018 × f2018	0.050	(0.012) ***	0.431	(0.021) ***
d2008 × f2007	0.020	(0.057)	0.772	(0.210) ***
d2009 × f2007	0.062	(0.060)	-0.290	(0.201)
d2009 × f2008	0.060	(0.060)	-0.199	(0.200)
d2010 × f2007	0.022	(0.054)	0.033	(0.088)
d2010 × f2008	0.085	(0.051) *	0.192	(0.071) ***
d2010 × f2009	0.136	(0.051) ***	0.350	(0.066) ***
d2011 × f2007	-0.033	(0.054)	-0.080	(0.093)
d2011 × f2008	-0.011	(0.048)	-0.044	(0.070)
d2011 × f2009	0.000	(0.048)	0.058	(0.065)
d2011 × f2010	0.053	(0.047)	0.242	(0.057) ***
d2012 × f2007	0.028	(0.055)	-0.002	(0.096)
d2012 × f2008	0.015	(0.047)	-0.043	(0.074)
d2012 × f2009	0.023	(0.045)	0.028	(0.067)
d2012 × f2010	0.034	(0.044)	0.091	(0.058)
d2012 × f2011	0.038	(0.042)	0.176	(0.050) ***
d2013 × f2007	-0.082	(0.054)	-0.137	(0.095)
d2013 × f2008	-0.059	(0.045)	-0.085	(0.069)
d2013 × f2009	-0.037	(0.042)	-0.096	(0.062)
d2013 × f2010	-0.052	(0.039)	-0.063	(0.053)
d2013 × f2011	-0.013	(0.037)	0.038	(0.047)
d2013 × f2012	0.018	(0.035)	0.142	(0.041) ***
Constant	0.629	(0.008) ***	1.523	(0.202) ***

N	459,318	117,279
N firms	115,989	17,705
Adj. R^2	0.166	0.326

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Worker-level event study results before aggregation by relative time

Dependent variable:	(1)		(2)	
ln(monthly wages)	No controls		Controls	
d2008 × f2008	0.051	(0.018) ***	0.027	(0.022)
d2008 × f2009	-0.018	(0.022)	-0.035	(0.025)
d2008 × f2010	-0.020	(0.025)	-0.035	(0.028)
d2008 × f2011	-0.062	(0.027) **	-0.081	(0.029) ***
d2008 × f2012	-0.054	(0.028) *	-0.069	(0.031) **
d2008 × f2013	-0.067	(0.030) **	-0.079	(0.032) **
d2008 × f2014	-0.061	(0.030) **	-0.077	(0.033) **
d2008 × f2015	-0.055	(0.033)	-0.054	(0.035)
d2008 × f2016	-0.005	(0.032)	-0.034	(0.035)
d2008 × f2017	-0.041	(0.038)	-0.071	(0.047)
d2008 × f2018	-0.050	(0.058)	-0.202	(0.073) ***
d2009 × f2009	0.072	(0.025) ***	0.030	(0.027)
d2009 × f2010	0.025	(0.028)	0.002	(0.030)
d2009 × f2011	0.022	(0.029)	0.009	(0.030)
d2009 × f2012	0.004	(0.030)	-0.001	(0.033)
d2009 × f2013	0.019	(0.031)	0.008	(0.034)
d2009 × f2014	0.031	(0.032)	0.031	(0.035)
d2009 × f2015	0.037	(0.034)	0.032	(0.038)

d2009 × f2016	0.010	(0.034)	0.007	(0.036)
d2009 × f2017	0.067	(0.036) *	0.060	(0.039)
d2009 × f2018	0.089	(0.046) *	0.105	(0.046) **
d2010 × f2010	0.122	(0.026) ***	0.085	(0.028) ***
d2010 × f2011	0.086	(0.026) ***	0.054	(0.028) *
d2010 × f2012	0.053	(0.027) *	0.018	(0.029)
d2010 × f2013	0.046	(0.027) *	0.014	(0.029)
d2010 × f2014	0.023	(0.028)	-0.021	(0.030)
d2010 × f2015	0.015	(0.029)	-0.030	(0.030)
d2010 × f2016	0.022	(0.029)	-0.025	(0.030)
d2010 × f2017	-0.007	(0.030)	-0.061	(0.031) **
d2010 × f2018	-0.061	(0.033) *	-0.105	(0.033) ***
d2011 × f2011	0.063	(0.025) **	0.032	(0.026)
d2011 × f2012	0.057	(0.025) **	0.034	(0.026)
d2011 × f2013	0.071	(0.025) ***	0.049	(0.026) *
d2011 × f2014	0.079	(0.025) ***	0.056	(0.026) **
d2011 × f2015	0.065	(0.025) **	0.039	(0.025)
d2011 × f2016	0.058	(0.025) **	0.036	(0.024)
d2011 × f2017	0.061	(0.025) **	0.059	(0.025) **
d2011 × f2018	0.047	(0.026) *	0.035	(0.024)
d2012 × f2012	0.047	(0.024) **	0.024	(0.025)
d2012 × f2013	0.005	(0.024)	-0.017	(0.025)
d2012 × f2014	-0.009	(0.024)	-0.024	(0.025)
d2012 × f2015	0.003	(0.024)	-0.008	(0.025)
d2012 × f2016	0.010	(0.022)	-0.006	(0.023)
d2012 × f2017	-0.002	(0.023)	-0.020	(0.024)
d2012 × f2018	0.014	(0.021)	0.001	(0.022)

d2013 × f2013	0.040	(0.023) *	0.053	(0.023) **
d2013 × f2014	0.012	(0.023)	0.032	(0.022)
d2013 × f2015	0.004	(0.022)	0.017	(0.022)
d2013 × f2016	0.002	(0.021)	0.014	(0.020)
d2013 × f2017	0.013	(0.020)	0.015	(0.019)
d2013 × f2018	0.015	(0.019)	0.013	(0.018)
d2014 × f2014	0.082	(0.022) ***	0.055	(0.021) ***
d2014 × f2015	0.062	(0.021) ***	0.047	(0.020) **
d2014 × f2016	0.038	(0.020) *	0.026	(0.019)
d2014 × f2017	0.028	(0.019)	0.022	(0.018)
d2014 × f2018	-0.006	(0.017)	-0.004	(0.016)
d2015 × f2015	0.050	(0.017) ***	0.041	(0.017) **
d2015 × f2016	0.033	(0.016) **	0.027	(0.016) *
d2015 × f2017	0.013	(0.015)	0.006	(0.015)
d2015 × f2018	0.020	(0.013)	0.010	(0.014)
d2016 × f2016	0.041	(0.013) ***	0.012	(0.013)
d2016 × f2017	0.008	(0.012)	-0.009	(0.012)
d2016 × f2018	0.030	(0.012) ***	0.014	(0.011)
d2017 × f2017	0.033	(0.014) **	0.034	(0.014) **
d2017 × f2018	-0.025	(0.012) **	-0.006	(0.012)
d2018 × f2018	0.008	(0.010)	0.001	(0.013)
d2008 × f2007	0.055	(0.016) ***	0.048	(0.018) ***
d2009 × f2007	-0.013	(0.021)	-0.021	(0.021)
d2009 × f2008	0.050	(0.023) **	0.031	(0.024)
d2010 × f2007	0.047	(0.024) **	0.040	(0.024) *
d2010 × f2008	0.029	(0.025)	0.017	(0.027)
d2010 × f2009	0.097	(0.026) ***	0.084	(0.027) ***

d2011 × f2007	-0.002	(0.027)	-0.014	(0.028)
d2011 × f2008	0.018	(0.026)	0.014	(0.027)
d2011 × f2009	0.020	(0.025)	-0.001	(0.026)
d2011 × f2010	0.038	(0.025)	0.017	(0.026)
d2012 × f2007	-0.021	(0.030)	-0.008	(0.031)
d2012 × f2008	-0.020	(0.026)	-0.013	(0.027)
d2012 × f2009	-0.018	(0.025)	-0.020	(0.026)
d2012 × f2010	0.007	(0.025)	0.004	(0.026)
d2012 × f2011	0.042	(0.024) *	0.029	(0.025)
d2013 × f2007	-0.053	(0.033)	-0.003	(0.034)
d2013 × f2008	-0.046	(0.029)	-0.024	(0.029)
d2013 × f2009	0.008	(0.027)	0.025	(0.027)
d2013 × f2010	-0.020	(0.026)	0.005	(0.026)
d2013 × f2011	0.003	(0.024)	0.031	(0.024)
d2013 × f2012	0.033	(0.024)	0.049	(0.024) **
Constant	7.561	(0.006) ***	7.654	(0.097) ***
N	652,432		210,083	
N firms	210,584		51,597	
Adj. R^2	0.053		0.081	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

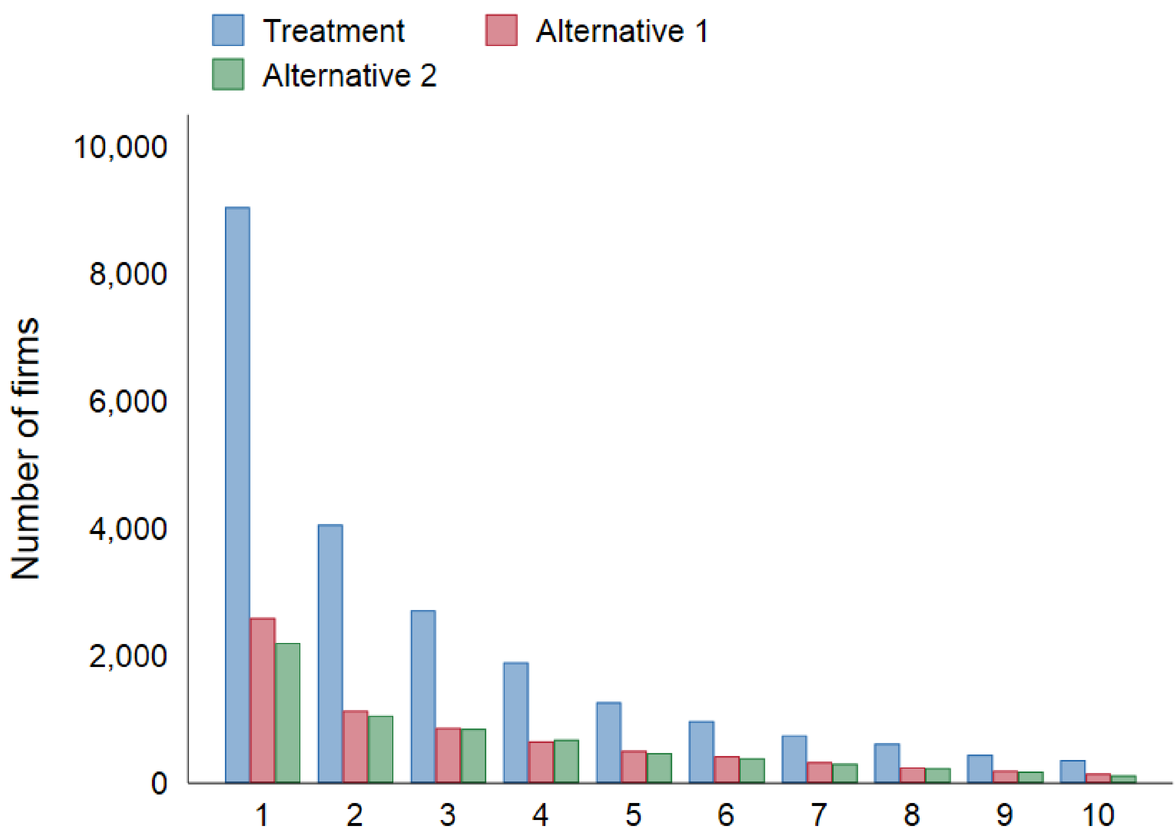
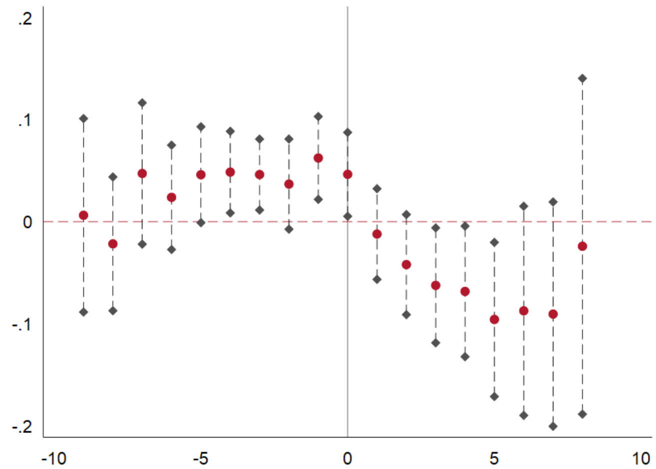
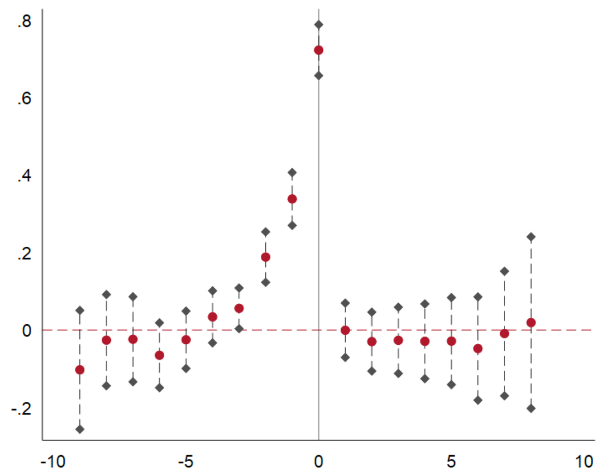


Figure 12: First former MNE worker by firm age: Original and alternative robustness definitions



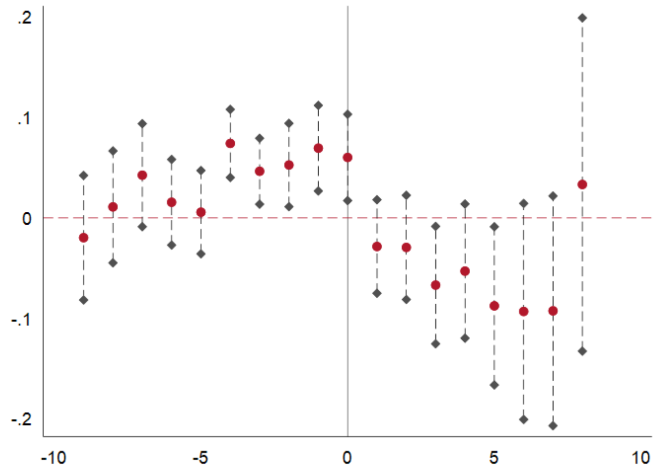
(a) Mean wages of founding workers



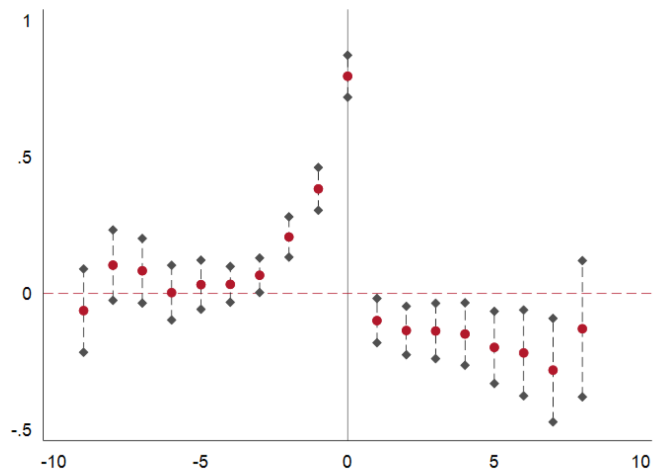
(b) Firm size

Figure 13: Robustness test 1 - Former MNE Manager joins (Firm-level analysis)

Notes: This figure shows firm-level event study results from Equation (3). The outcome variables listed in the sub-captions are are regressed on time periods, the aggregated coefficients of which are shown in the graphs. Outcomes are relative to the first time period in the series (omitted). Confidence intervals are at the 95th percentile. Source: Own calculations based on CSO data described in Section 2.2.



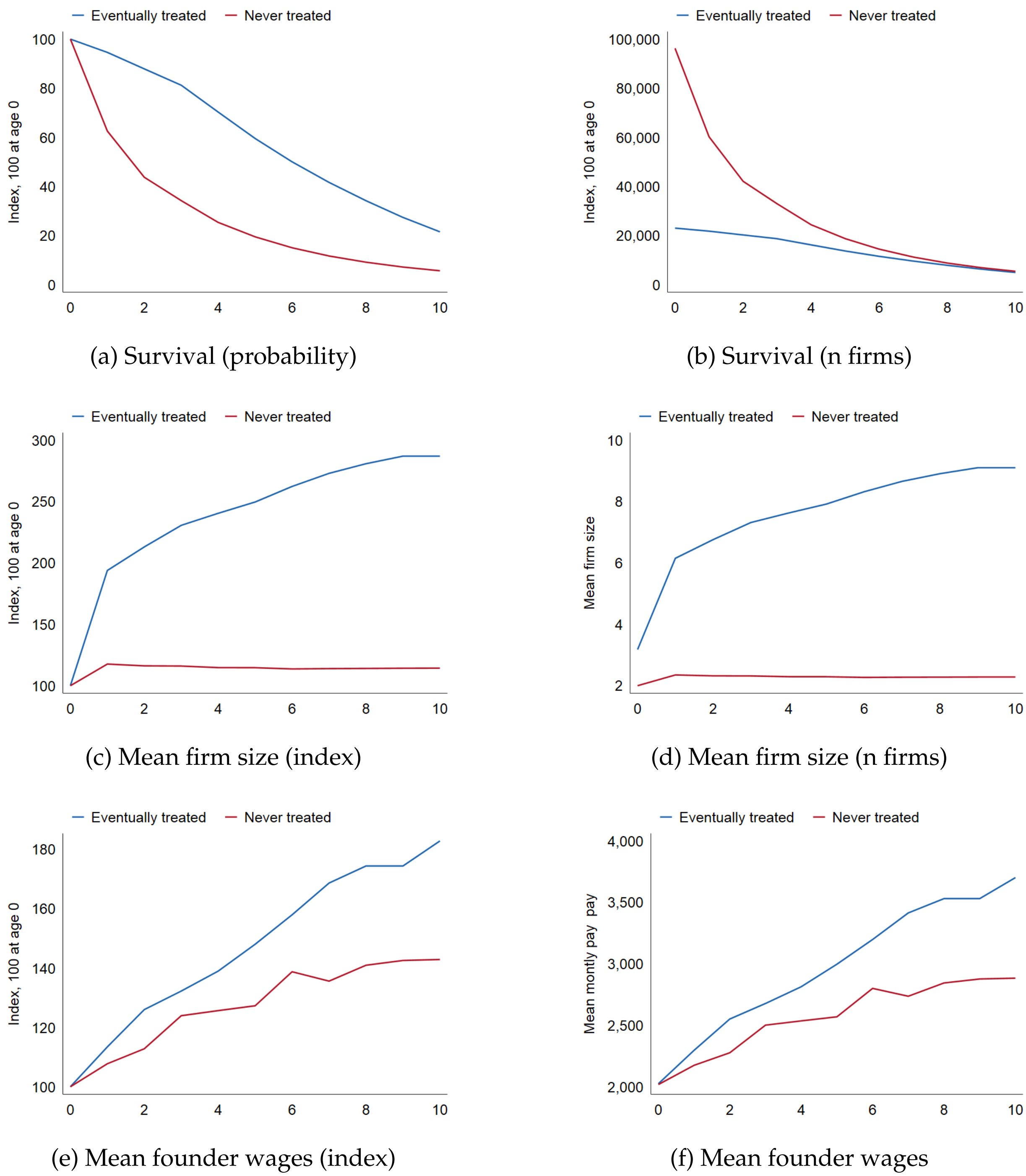
(a) Mean wages of founding workers



(b) Firm size

Figure 14: Robustness test 2 - Former MNE worker, current manager joins (Firm-level analysis)

Notes: This figure shows firm-level event study results from Equation (3). The outcome variables listed in the sub-captions are are regressed on time periods, the aggregated coefficients of which are shown in the graphs. Outcomes are relative to the first time period in the series (omitted). Confidence intervals are at the 95th percentile. Source: Own calculations based on CSO data described in Section 2.2.



(a) Survival (probability)

(b) Survival (n firms)

(c) Mean firm size (index)

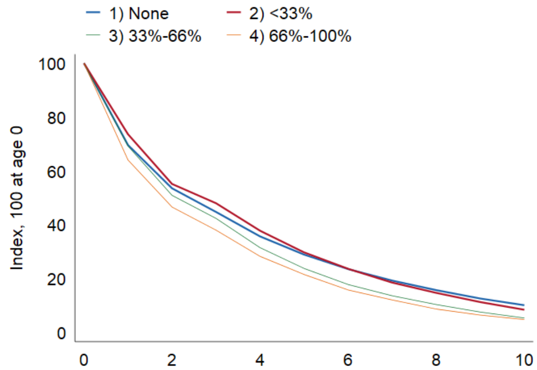
(d) Mean firm size (n firms)

(e) Mean founder wages (index)

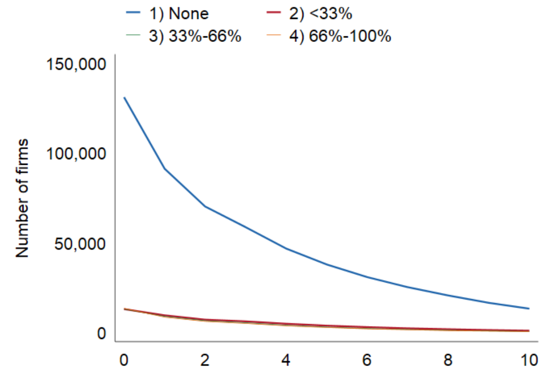
(f) Mean founder wages

Figure 15: Mean firm outcomes by ever treated and never treated

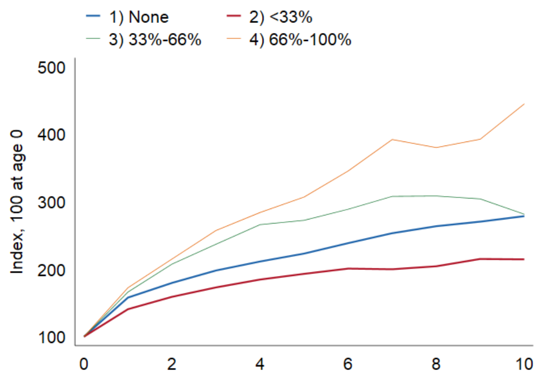
Notes: This figure shows outcomes for startup firms that are eventually treated (where a former MNE worker joins the firm at some stage during their observed existence) or never treated. Firms that are eventually treated have higher survival probabilities, grow more on average and their founding workers benefit from higher wages. Source: own calculations based on the administrative data described in Section 2.2.



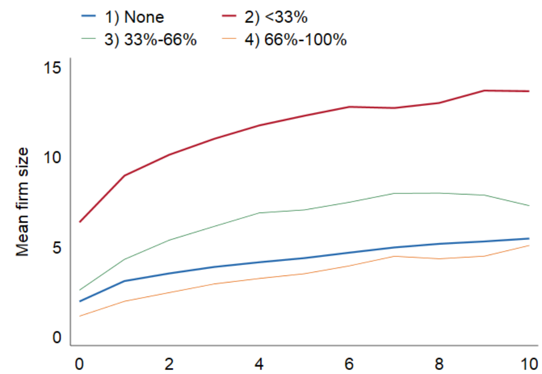
(a) Survival (probability)



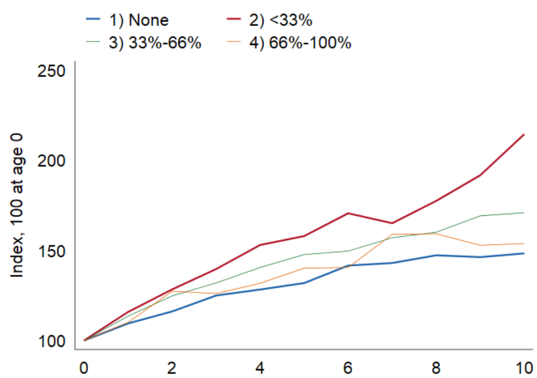
(b) Survival (n firms)



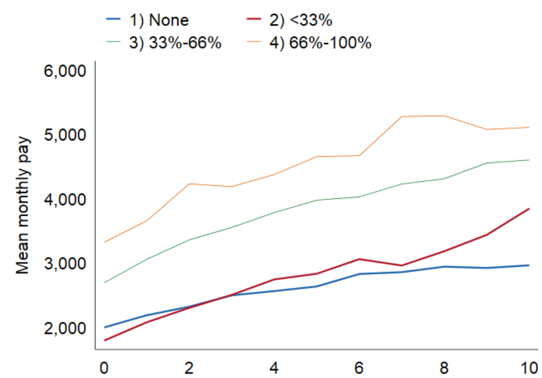
(c) Mean firm size (index)



(d) Mean firm size (n workers)



(e) Mean founder wages (index)



(f) Mean founder wages (euro)

Figure 16: Firm outcomes grouped by shares of former MNE founding workers

Notes: This figure shows mean firm outcomes grouped by share of former MNE workers defined in Section 2.7. Group 1 includes firms that have no former MNE workers in their first year of existence, while groups 2,3 and 4 are grouped by tercile of the remaining workers. Source: own calculations based on the administrative data described in Section 2.2.

Table 8: Founder regressions (with controls)

(a) Firm exit

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Group 2	0.038 **	0.037 **	-0.006	0.026 **	0.034 **	0.039 **	0.055 **	0.037 **	0.055 **	0.062 **
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.011)	(0.013)
Group 3	0.021 **	0.035 **	0.006	0.045 **	0.052 **	0.049 **	0.048 **	0.043 **	0.054 **	0.074 **
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.012)	(0.014)
Group 4	0.050 **	0.046 **	0.019 **	0.052 **	0.033 **	0.073 **	0.033 **	0.067 **	0.045 **	0.040 **
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.011)	(0.013)	(0.015)
Constant	0.337 **	0.272 **	0.222 **	0.254 **	0.242 **	0.241 **	0.239 **	0.237 **	0.260 **	0.254 **
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
N	170,933	122,602	94,045	78,612	62,195	49,794	40,026	32,450	26,251	20,811
R^2	0.016	0.012	0.014	0.014	0.013	0.016	0.018	0.021	0.025	0.021
Mean DV	0.305	0.031	0.054	0.057	0.060	0.064	0.066	0.068	0.069	0.070

(b) Firm size

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Group 2	5.311 **	5.975 **	6.411 **	6.888 **	7.141 **	7.296 **	6.859 **	6.887 **	7.381 **	7.159 **
	(0.071)	(0.111)	(0.137)	(0.172)	(0.196)	(0.265)	(0.348)	(0.392)	(0.466)	(0.566)
Group 3	1.209 **	1.764 **	2.130 **	2.437 **	2.481 **	2.558 **	2.635 **	2.380 **	2.191 **	1.374 *
	(0.073)	(0.115)	(0.145)	(0.187)	(0.217)	(0.300)	(0.399)	(0.459)	(0.559)	(0.699)
Group 4	-0.782 **	-0.711 **	-0.655 **	-0.554 **	-0.658 **	-0.706 *	-0.529	-0.931 $^{(*)}$	-1.076 $^{(*)}$	-0.799
	(0.076)	(0.120)	(0.152)	(0.196)	(0.226)	(0.319)	(0.425)	(0.502)	(0.609)	(0.741)
Constant	3.110 **	3.547 **	3.925 **	4.194 **	4.429 **	4.745 **	5.048 **	5.258 **	5.394 **	5.561 **
	(0.022)	(0.034)	(0.042)	(0.053)	(0.059)	(0.079)	(0.102)	(0.114)	(0.133)	(0.156)
N	118,785	90,534	75,783	59,797	47,976	38,573	31,242	25,227	20,021	15,879
R^2	0.090	0.073	0.071	0.066	0.069	0.052	0.040	0.045	0.044	0.041
Mean DV	3.578	3.931	4.099	4.157	4.118	4.110	4.119	4.106	4.093	4.101

Notes: This table displays the coefficients $\beta_{2t}, \ldots, \beta_{4t}$ from Equation (5). The outcome listed at the top of each panel is regressed on indicators for groups 2-4 based on their share of former MNE workers in their first year.

For the exiting variable in Panel (a), the outcome equals one if a startup firm exited in year t, and zero otherwise. Here, β_{4t} measures the probability that a firm in the group with the highest share of former MNE workers exited aged t conditional on having survived until period t. The coefficients of the dummy variables measure the difference in this probability between the respective greoup and the bottom group (firms with no former MNE workers in their first year).

Δ firm size in Panel (b) is defined as the difference between firm size in age t and age 0. Here, β_{4t} measures the average change in the outcome in the group with the highest share of former MNE workers between age 0 and age t. The coefficients of the dummy variables measure the change in the outcome between age 0 and t in group k relative to firms with no former MNE workers in their first year. A positive coefficient β_{kt} means that the average outcome in group k increased more — or decreased less — than the average outcome in the bottom group.

Mean DV refers to the mean value of the dependent variable. Standard errors in parentheses: $^{(*)}$ $p< 0.10$, * $p< 0.05$, ** $p<0.01$.

Table 9: Founder regressions (with controls)

Δ Firm size

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Bracket 2	-0.138 **	-0.176 **	-0.185 **	-0.193 **	-0.189 **	-0.195 **	-0.220 **	-0.224 **	-0.215 **	-0.241 **
	(0.006)	(0.009)	(0.010)	(0.012)	(0.014)	(0.016)	(0.019)	(0.021)	(0.025)	(0.029)
Bracket 3	-0.035 **	-0.024 **	-0.002	0.009	0.021	0.035 (*)	0.017	0.030	0.026	0.016
	(0.007)	(0.009)	(0.011)	(0.013)	(0.015)	(0.018)	(0.022)	(0.025)	(0.030)	(0.036)
Bracket 4	0.047 **	0.091 **	0.128 **	0.163 **	0.161 **	0.185 **	0.204 **	0.229 **	0.195 **	0.231 **
	(0.007)	(0.009)	(0.011)	(0.014)	(0.016)	(0.020)	(0.023)	(0.027)	(0.032)	(0.038)
Constant	0.238 **	0.308 **	0.353 **	0.384 **	0.404 **	0.417 **	0.429 **	0.438 **	0.439 **	0.435 **
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
N	118,785	90,533	75,782	59,796	47,975	38,571	31,241	25,226	20,021	15,877
R^2	0.023	0.026	0.030	0.031	0.031	0.033	0.036	0.041	0.046	0.052
Mean DV	0.805	0.887	0.921	0.934	0.938	0.945	0.952	0.956	0.966	0.971

(b) Firm mean founder monthly pay

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Group 2	0.021 **	0.057 **	0.067 **	0.091 **	0.113 **	0.119 **	0.106 **	0.121 **	0.112 **	0.100 **
	(0.006)	(0.009)	(0.011)	(0.013)	(0.015)	(0.018)	(0.020)	(0.023)	(0.026)	(0.029)
Group 3	0.037 **	0.065 **	0.092 **	0.109 **	0.148 **	0.136 **	0.154 **	0.155 **	0.160 **	0.199 **
	(0.006)	(0.008)	(0.010)	(0.013)	(0.016)	(0.019)	(0.022)	(0.026)	(0.030)	(0.035)
Group 4	0.035 **	0.075 **	0.079 **	0.094 **	0.132 **	0.142 **	0.162 **	0.135 **	0.128 **	0.151 **
	(0.006)	(0.009)	(0.011)	(0.014)	(0.017)	(0.020)	(0.024)	(0.028)	(0.033)	(0.037)
Constant	0.052 **	0.083 **	0.111 **	0.130 **	0.137 **	0.146 **	0.147 **	0.157 **	0.133 **	0.130 **
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.012)
N	109,428	75,650	59,300	44,429	34,019	26,369	20,589	16,080	12,230	9,330
R^2	0.005	0.008	0.009	0.012	0.015	0.017	0.021	0.024	0.030	0.033
Mean DV	7.399	7.481	7.512	7.527	7.541	7.557	7.573	7.588	7.618	7.638

Notes: This table displays the coefficients $\beta_{2t}, \ldots, \beta_{4t}$ from Equation (5). The outcome listed at the top of each panel is regressed on indicators for groups 2-4 based on their share of former MNE workers in their first year.
For the exiting variable in Panel (a), the outcome equals one if a startup firm exited in year t, and zero otherwise. Here, β_{4t} measures the probability that a firm in the group with the highest share of former MNE workers exited aged t conditional on having survived until period t. The coefficients of the dummy variables measure the difference in this probability between the respective greoup and the bottom group (firms with no former MNE workers in their first year).
Δ firm size in Panel (b) is defined as the difference between firm size in age t and age 0. Here, β_{4t} measures the average change in the outcome in the group with the highest share of former MNE workers between age 0 and age t. The coefficients of the dummy variables measure the change in the outcome between age 0 and t in group k relative to firms with no former MNE workers in their first year. A positive coefficient β_{kt} means that the average outcome in group k increased more — or decreased less — than the average outcome in the bottom group.
Mean DV refers to the mean value of the dependent variable. Standard errors in parentheses: $^{(*)}$ $p< 0.10$, * $p< 0.05$, ** $p<0.01$.

Table 10: Founder regressions (no controls)

(a) Firm exit

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Bracket 2	-0.040 **	0.002	-0.057 **	-0.011 *	0.001	-0.000	0.013 (*)	0.002	0.010	0.030 **
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.011)
Bracket 3	0.003	0.023 **	-0.007	0.036 **	0.046 **	0.042 **	0.048 **	0.044 **	0.054 **	0.078 **
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.012)	(0.014)
Bracket 4	0.056 **	0.044 **	0.021 **	0.055 **	0.040 **	0.078 **	0.051 **	0.084 **	0.061 **	0.052 **
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.012)	(0.014)
Constant	0.303 **	0.256 **	0.198 **	0.234 **	0.223 **	0.218 **	0.213 **	0.216 **	0.231 **	0.229 **
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
N	170,933	122,602	94,046	78,613	62,196	49,795	40,028	32,451	26,251	20,811
R^2	0.002	0.001	0.002	0.002	0.001	0.002	0.001	0.002	0.002	0.002
Mean DV	0.305	0.031	0.054	0.057	0.060	0.064	0.066	0.068	0.069	0.070

(b) Firm size

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Bracket 2	5.865 **	6.620 **	7.142 **	7.640 **	7.941 **	8.105 **	7.742 **	7.825 **	8.352 **	8.145 **
	(0.072)	(0.111)	(0.137)	(0.172)	(0.196)	(0.264)	(0.347)	(0.392)	(0.466)	(0.566)
Bracket 3	1.158 **	1.759 **	2.177 **	2.520 **	2.606 **	2.804 **	3.005 **	2.801 **	2.614 **	2.001 **
	(0.074)	(0.115)	(0.145)	(0.187)	(0.218)	(0.299)	(0.398)	(0.459)	(0.557)	(0.695)
Bracket 4	-1.083 **	-1.003 **	-0.892 **	-0.736 **	-0.840 **	-0.790 *	-0.540	-0.878 (*)	-0.916	-0.551
	(0.075)	(0.119)	(0.150)	(0.195)	(0.224)	(0.316)	(0.420)	(0.497)	(0.601)	(0.732)
Constant	3.091 **	3.516 **	3.876 **	4.137 **	4.366 **	4.669 **	4.958 **	5.160 **	5.293 **	5.453 **
	(0.022)	(0.034)	(0.043)	(0.053)	(0.060)	(0.080)	(0.103)	(0.115)	(0.134)	(0.158)
N	118,785	90,534	75,783	59,797	47,976	38,573	31,242	25,227	20,021	15,879
R^2	0.058	0.041	0.038	0.034	0.036	0.026	0.017	0.017	0.017	0.013
Mean DV	3.578	3.931	4.099	4.157	4.118	4.110	4.119	4.106	4.093	4.101

Notes: This table displays the coefficients $\beta_{2t}, \ldots, \beta_{4t}$ from Equation (5). The outcome listed at the top of each panel is regressed on indicators for groups 2-4 based on their share of former MNE workers in their first year.
For the exiting variable in Panel (a), the outcome equals one if a startup firm exited in year t, and zero otherwise. Here, β_{4t} measures the probability that a firm in the group with the highest share of former MNE workers exited aged t conditional on having survived until period t. The coefficients of the dummy variables measure the difference in this probability between the respective greoup and the bottom group (firms with no former MNE workers in their first year).
Δ firm size in Panel (b) is defined as the difference between firm size in age t and age 0. Here, β_{4t} measures the average change in the outcome in the group with the highest share of former MNE workers between age 0 and age t. The coefficients of the dummy variables measure the change in the outcome between age 0 and t in group k relative to firms with no former MNE workers in their first year. A positive coefficient β_{kt} means that the average outcome in group k increased more — or decreased less — than the average outcome in the bottom group.
Mean DV refers to the mean value of the dependent variable. Standard errors in parentheses: $^{(*)}$ $p< 0.10$, * $p< 0.05$, ** $p<0.01$.

Table 11: Founder regressions (no controls)

Δ Firm size

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Group 2	-0.093 **	-0.123 **	-0.127 **	-0.134 **	-0.129 **	-0.134 **	-0.152 **	-0.153 **	-0.139 **	-0.162 **
	(0.006)	(0.009)	(0.010)	(0.012)	(0.014)	(0.016)	(0.019)	(0.021)	(0.025)	(0.029)
Group 3	-0.037 **	-0.022 *	0.000	0.013	0.030 *	0.055 **	0.043 *	0.061 *	0.070 *	0.069 (*)
	(0.006)	(0.009)	(0.011)	(0.013)	(0.015)	(0.018)	(0.022)	(0.025)	(0.030)	(0.036)
Group 4	0.022 **	0.068 **	0.103 **	0.140 **	0.144 **	0.180 **	0.209 **	0.238 **	0.213 **	0.254 **
	(0.007)	(0.009)	(0.011)	(0.013)	(0.016)	(0.019)	(0.023)	(0.027)	(0.032)	(0.038)
Constant	0.236 **	0.306 **	0.350 **	0.380 **	0.400 **	0.411 **	0.422 **	0.430 **	0.430 **	0.426 **
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
N	118,785	90,534	75,783	59,797	47,976	38,573	31,242	25,227	20,021	15,879
R^2	0.002	0.003	0.004	0.004	0.004	0.005	0.005	0.006	0.004	0.005
Mean DV	0.805	0.887	0.921	0.934	0.938	0.945	0.952	0.956	0.966	0.971

(b) Firm mean founder monthly pay

	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10
Group 2	0.060 **	0.107 **	0.115 **	0.140 **	0.163 **	0.172 **	0.165 **	0.177 **	0.192 **	0.193 **
	(0.005)	(0.008)	(0.009)	(0.011)	(0.013)	(0.016)	(0.018)	(0.020)	(0.023)	(0.026)
Group 3	0.039 **	0.067 **	0.093 **	0.113 **	0.156 **	0.150 **	0.173 **	0.185 **	0.198 **	0.239 **
	(0.006)	(0.008)	(0.010)	(0.013)	(0.016)	(0.019)	(0.022)	(0.025)	(0.030)	(0.035)
Group 4	0.020 **	0.055 **	0.057 **	0.075 **	0.121 **	0.137 **	0.168 **	0.158 **	0.149 **	0.174 **
	(0.006)	(0.009)	(0.011)	(0.013)	(0.016)	(0.020)	(0.023)	(0.028)	(0.032)	(0.036)
Constant	0.071 **	0.106 **	0.134 **	0.151 **	0.157 **	0.169 **	0.172 **	0.178 **	0.170 **	0.171 **
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
N	109,428	75,651	59,301	44,430	34,020	26,371	20,590	16,082	12,231	9,337
R^2	0.001	0.004	0.004	0.005	0.008	0.008	0.008	0.009	0.010	0.012
Mean DV	7.399	7.481	7.512	7.527	7.541	7.557	7.573	7.588	7.618	7.638

Notes: This table displays the coefficients $\beta_{2t}, \ldots, \beta_{4t}$ from Equation (5). The outcome listed at the top of each panel is regressed on indicators for groups 2-4 based on their share of former MNE workers in their first year.

For the exiting variable in Panel (a), the outcome equals one if a startup firm exited in year t, and zero otherwise. Here, β_{4t} measures the probability that a firm in the group with the highest share of former MNE workers exited aged t conditional on having survived until period t. The coefficients of the dummy variables measure the difference in this probability between the respective greoup and the bottom group (firms with no former MNE workers in their first year).

Δ firm size in Panel (b) is defined as the difference between firm size in age t and age 0. Here, β_{4t} measures the average change in the outcome in the group with the highest share of former MNE workers between age 0 and age t. The coefficients of the dummy variables measure the change in the outcome between age 0 and t in group k relative to firms with no former MNE workers in their first year. A positive coefficient β_{kt} means that the average outcome in group k increased more — or decreased less — than the average outcome in the bottom group.

Mean DV refers to the mean value of the dependent variable. Standard errors in parentheses: $^{(*)}$ $p< 0.10$, * $p< 0.05$, ** $p<0.01$.

6.1 Variable descriptions

$Wage_{ijt}$ - Worker's monthly taxable pay in euros from their main employer in a given year, deflated using the Consumer Price Index.

lnY_{ijt} - Log of $Wage_{ijt}$

Age_{ijt} - Worker age.

$Female_{ijt}$ - Dummy variable for whether worker is female.

$FirmSize_j$ - ln(firm size), measured by number of workers.

$NonIrish_{ijt}$ - Anyone with non-Irish nationality, as recorded by the Irish Department of Social Protection when assigning someone with a Personal Public Service (PPS) number. The nationality recorded must be supported by documentation such as a birth certificate or passport from the person's country of origin.

$Weeks_{ijt}$ - Total number of weeks of employment per year that are liable for social insurance contributions.

$Industry_{jt}$ - Three digit NACE rev. 2 industry code.

$FirmAge_{jt}$ - Firm age.

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