DISCUSSION PAPER SERIES

DP12167

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INDUSTRIAL ORGANIZATION

ISSN 0265-8003

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Discussion Paper DP12167
Published 20 July 2017
Submitted 20 July 2017

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Abstract

We use a comprehensive sample of takeovers in Belgium to show that they are remarkably common and an important part of many firms' growth process. They affect both small and large firms and, over a five-year period, 17 percent of private employment. We estimate the impact of takeovers on employment growth of the merged entity using an empirical framework that explicitly takes into account that mergers are formed by pairs of firms. It allows for post-merger employment outcomes that are heterogeneous and determined jointly by the characteristics of both partners. The average merger is estimated to reduce employment by 8% over a four-year period, but the contraction can be three times as large for some types of mergers, while employment expands for other types.

JEL Classification: J23, L23

Keywords: merger, M&A, Firm Dynamics, Matching, efficiency defense

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Acknowledgements
We would like to thank several people for valuable comments and suggestions: Eric Bartelsman, John Earle, Joep Konings, Otto Toivanen. The authors are grateful to the Belgian National Social Security Office and to Statistics Belgium for providing the data. This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No. 649378 and KU Leuven Program Financing.

Employment growth following takeovers

Karen Geurts Johannes Van Biesebroeck*

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We use a comprehensive sample of takeovers in Belgium to show that they are remarkably common and an important part of many firms' growth process. They affect both small and large firms and, over a five-year period, 17 percent of private employment. We estimate the impact of takeovers on employment growth of the merged entity using an empirical framework that explicitly takes into account that mergers are formed by pairs of firms. It allows for post-merger employment outcomes that are heterogeneous and determined jointly by the characteristics of both partners. The average merger is estimated to reduce employment by 8% over a four-year period, but the contraction can be three times as large for some types of mergers, while employment expands for other types.

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1. Introduction

A large literature has studied the effect of mergers and acquisitions on employment, especially in the context of foreign takeovers, but little consensus has emerged regarding their effects.[1] While studies that find a negative effect on employment in takeover targets outnumber those that find evidence of employment expansions, effects in acquiring firms could compensate for this, but estimates for them are equally ambiguous.[2]

Three studies have looked at the evolution of total employment for the merged entities, but estimates are again inconclusive. On a sample of all mergers involving workers covered by the Michigan unemployment insurance system between 1978 and 1984, Brown and Medoff (1988) find that mergers lead to employment expansions, at least when the firms integrate their workforces. In contrast, on a sample of 442 domestic mergers initiated by large UK firms over a 30-year period, Conyon et al. (2002) document a sharply reduced demand for labor, even controlling for output changes. Finally, Gugler and Yurtoglu (2004) study only mergers that involve a listed acquirer and find negative employment effects for European, but not for US firms.

These employment effects are potentially important, as we show that takeover activity is a more dynamic and frequent process than often portrayed, affecting both small and large firms. On our comprehensive sample of takeovers in the Belgian domestic market, we count 2,601 mergers over a seven-year period, involving 6,000 firms as acquirer or target.[3] Aggregate effects could be important as these firms tend to be larger than average. We calculate that in an average five-year period 17 percent of private sector employees work for a firm that is

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[1] Girma and Görg (2004), for example, show that foreign takeovers reduce employment growth of domestic plants in the UK electronics sector, but not in the food sector; just as Lehto and Böckerman (2008) find negative employment effects for Finnish manufacturing plants, but not in services. Bandick and Görg (2010) even find some evidence of an employment expansion in Swedish targets, but only for exporters in vertical takeovers, while McGuckin and Nguyen (2001) find positive effects more generally for US manufacturing, except in the case of the largest plants, not distinguishing between foreign and domestic takeovers.

[2] Stiebale and Trax (2011) find no significant effects on the domestic employment of French or UK acquirers, while Furlan (2015) finds a positive effect in a sample of European takeovers.

[3] The distinction between mergers and takeovers or acquisitions is essentially a legal one without a clear-cut difference in an economic sense. Similar to previous work, we do not discern between them and use the terms interchangeably.

involved in a takeover. If takeovers would systematically increase or reduce firms' demand for labor, the impact on the labor market would be considerable.

To identify the employment effect of mergers, we need to take a stand on the following three questions: (1) How can we identify a merger? (2) What is a proper control for a newly created firm? (3) Why did the firms merge? These questions lead to important measurement issues that help explain the wide range of estimates obtained in the literature. We make contributions dealing with each of these three measurement challenges.

First, one reason for conflicting results is that the sample of mergers differs greatly across studies. Some only look at a relatively small number of mergers by large, often listed firms, while others use innovative methods or unique data to obtain a record of "all" mergers in a target population, in the latter group are Brown and Medoff (1988), Lehto and Böckerman (2008), and Burghardt and Helm (2015). Our objective is to identify the universe of firm-level reorganizations that are an integral part of firms' growth process. We complement filings at the Commercial Court with instances where we observe in the Belgian social security records that workforces of two firms are combined or that a substantial fraction of the workforce moves from one firm to another (Geurts, 2016).[4] We do not include strategic mergers, often motivated by firm diversification or market power, where the original firms continue to operate independently. We believe the process of firm integration is an important and understudied way that growth takes place in the economy. In the process of constructing a control sample of potential mergers, we document new insights about "who merges with whom."

Second, previous studies have traced the employment evolution of targets, acquirers, or the total for the merged firms. The latter is preferable in our setting as employment effects are likely to be asymmetric for targets and acquirers, and can even offset if jobs are reallocated between the two merging entities. To deal with endogeneity, most recent studies rely on the selection-on-observables assumption and use a matching estimator comparing the employment evolution of merging firms to a counterfactual evolution (Imbens and Wooldridge, 2009).[5] Existing studies use single firms that are comparable in characteristics to one of the merging

[4] This data constitutes the universe of the employer-employee records for the private sector in Belgium.

[5] Even though endogeneity of mergers is clearly important, it is sometimes ignored because it has proven virtually impossible to find good instruments. Any variable correlated with a firm's decision to engage in a merger is likely to be correlated with post-merger firm performance.

firms as counterfactual. Mergers, however, are formed by pairs of firms with different characteristics, making single firms inappropriate counterfactuals. Instead, we use as control group simulated pairs of non-merging firms that match a set of pre-merger characteristics of both the target and the acquirer. This way we obtain a comparable post-merger employment outcome in the case the two firms would not have merged. This 'dyadic' approach has been used in the strategic alliance literature where alliance formation is explicitly modelled as determined jointly by both partners' preferences and characteristics (Chung, Singh and Lee, 2000). It specifically takes into account that the characteristics of both the target and the acquirer affect the decision to engage in a takeover and we can even let the post-merger growth patterns depend on these combined features.

Third, the literature discusses a variety of motivations for mergers with potentially different effects on employment.[6] Two employment-reducing effects have featured prominently: (i) increased market power is likely to reduce output and thus employment, and (ii) a new management team is less likely to be committed to upholding past contracts with stakeholders (Shleifer and Summers, 1988). In contrast, Röller et al. (2001) discuss how different types of efficiency gains can have negative or positive effects on employment.[7] Kalnins et al. (2017) show that hotel mergers raise capacity utilization (occupancy) and have the potential to boost employment. Merely including control variables in the regression that describes the employment effect of a representative merger fails to capture this richness. Our control group of simulated firm pairs does not constrain us to estimate a single effect, but allows flexibly for heterogeneous effects of mergers depending on the circumstances. We use detailed target firm and acquirer characteristics as well as their interactions to identify an appropriate control group, as well as to allow the employment effect of a merger vary along those dimensions.[8]

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[6] Motivations for mergers discussed in the literature include saving on labor costs, realizing synergies, improving management and control, increasing market power, or benefitting from tax incentives. Non-profit maximizing motives, such as spending free cash flow, might also play a role (Jarrell et al. 1988; Jensen 1988).

[7] Eliminating duplication in headquarter services will reduce employment, but a merger that raises labor productivity will increase output and employment if the demand elasticity is sufficiently high. Lower capital costs for small firms or higher bargaining power to negotiate down prices of intermediate inputs are two other mechanisms that can raise employment.

[8] These include the detailed industry affiliation of both firms, their size and pre-merger growth performance, and their corporate structure.

Beyond the methodological innovations, we also report a number of novel economic findings. First, mergers that lead to workforce integration are a lot more common than one might expect, affecting on average 0.74% of firms and 4.29% of workers each year. More than one third of these events are not detected from filings at the Commercial Court, but show up in the employee-flows. Second, the average merger reduces employment by 2.33% in merging firms compared to an observationally equivalent pair of non-merging firms. These employment losses accumulate to 8.28% from the year before to three years after the merger. Third, we find evidence of substantial heterogeneity. The average employment outcome over the 71 sub-groups where we have enough observations to estimate a separate takeover effect ranges from -18% to +6%. Fourth, to understand mergers with unusual employment effects it is important to consider the characteristics of targets and acquirers jointly. For example, we find that a takeover of a target firm with above-average growth for its industry by an acquirer from a declining industry that is part of an enterprise group leads to an employment expansion for the newly created firm. However, takeovers of targets with below-average growth or by acquirers from a growing industry show employment effects that do not differ from the average.

The remainder of the paper is organized as follows. In Section 2 we outline our estimation framework and in Section 3 we introduce the data. In Section 4 we describe how we identify mergers and how we construct an appropriate control group; we also document the characteristics of merging firms. In Section 5 we show employment effects of mergers, first the average effect, and then the effects by type of mergers. Section 6 concludes.

2. Estimation framework

To evaluate the impact of takeovers on post-merger employment, we combine elements from three separate strands in the literature. First, we use as dependent variable the sum of employment of the two firms entering a merger rather than looking only at target firms or acquirers. Second, we use the sum of employment for simulated pairs of firms with similar characteristics as the merging firms as counterfactual in the comparison rather than comparing with the employment evolution of individual firms. Third, we use a treatment effects estimator that exactly matches on discrete covariates of both the target firm and acquirer to find comparable pairs of firms rather than using the propensity score. We now describe these three modeling choices in greater detail and highlight their advantages.

2.1. Dependent variable: total employment

Most previous studies restrict their analysis only to post-merger outcomes for the target plants or firms. This is a natural choice if one is interested in studying the effects of acquisitions of domestic plants by foreign multinationals, but it is ill-suited for our interest in the role of domestic takeovers or mergers in the firm growth process. Takeovers may very well affect employment of the acquiring firm, as it is common for jobs or entire departments to be reorganized or reallocated across the merged entities (Furlan, 2015). Merely taking into account the jobs that are lost (or gained) in the target firm, may under or overestimate the overall employment impact.

A straightforward solution by Brown and Medoff (1988) and Conyon et al. (2002) is to estimate the employment impact at the level of the combined entity, i.e. on total employment at the target and acquirer firms combined. Gugler and Yurtoglu (2004) follow the same approach and additionally take into account that firms often undertake multiple mergers or divestitures and they incorporate information on the entire merger history of firms.

In each of these three studies, the other observations included in the regression, and thus the implicit comparison group, are all the non-merging firms from the respective datasets, or in the case of Conyon et al. (2002) a random sample stratified by industry. They include control variables in the regression to hold constant differences between the characteristics of the control firms and those of the combined firms.

This approach disregards that takeovers are formed by two firms with different characteristics before the merger and these differences might be important for subsequent performance. Specific combinations of target and acquirer characteristics may reflect different types of mergers. For example, a large pharmaceutical company taking over a small, high-growth IT firm, is likely to have a different motivation and different post-merger strategy than two competitors joining in a horizontal merger. Yet, they are treated as similar events. Moreover, prior to the merger the two constituting firms are by construction smaller than control observations that have the same size as the combined entity. If employment growth depends on firm size, pre-merger size controls cannot appropriately control simultaneously for the expected combined growth rate of the merging firms, which were operating independently prior to the merger, as well as for the growth rate of the larger control firms.

2.2. Control group: simulated pairs of comparable firms

To estimate the impact of takeovers on post-merger employment, we need a valid control group to construct a counterfactual employment evolution. We consider explicitly that takeovers consist of two firms and choose pairs of firms that do not integrate as comparison group. This so-called 'dyadic' approach has been used in the strategic alliance literature which evaluates the performance of research joint ventures (Chung, Singh and Lee 2000; Mindruta, Moeen and Agarwal 2015). These are relationships between two independent organizations that choose to combine forces depending on the strengths and capabilities of both partners, much like mergers. The formation of alliances is modeled as jointly determined by the characteristics of both partners.

In line with this approach, we use as counterfactuals for the takeovers in our sample all simulated pairs of non-merging firms that share pre-merger features with the target and the acquirer firms. This approach has three advantages compared to previous merger evaluations. First, pairs of non-merging firms provide a more valid counterfactual than single firms to represent the potential post-merger employment outcome in the absence of the merger. Second, it allows us to model the probability of a merger as a function of the characteristics of both firms, target and acquirer, as well as on the interactions between both firms' characteristics. Existing studies that use a matching estimator model either the probability of a firm becoming a target or a firm becoming an acquirer, each time only as a function of the firm's own characteristics. Third, as we estimate a counterfactual employment for each merger, we do not need to limit ourselves to the impact of a representative merger, but we can allow for different 'types' of mergers, defined based on a combination of target and acquirer characteristics, to have unique employment effects. Given that some mergers are motivated by market power or consolidation waves, while other mergers aim to combine key assets and strengthen the growth potential of the merged firms, it is not implausible that different mergers have different employment effects.

The set of paired non-merging firms that we simulate contains all possible combinations of two firms where one satisfies the preconditions of an acquirer and the other those of a target.[9] The treatment effects estimator we introduce below requires a condition of common support.

[9] We impose that both firms in the pair cannot be the same firm and that they cannot be part of a merger themselves.

We are only able to calculate a valid counterfactual if conditional on the set of covariates the probability to be included in a merger is strictly larger than zero and below one. A large subset of firms in our dataset have characteristics that are virtually never observed for merging firms. Specifically, very small or very young firms, which constitute the majority of firms in the sample, are rarely involved in a takeover. We therefore restrict the sample of actual and potential acquirers to firms with at least 10 employees and at least three years of age in the year before a takeover, and the sample of targets to firms with at least 2 employees and at least one year in existence in *t*-1. This initial reduction of the sample can be considered as a pre-selection on observable characteristics.

To learn which characteristics are important determinants of the likelihood of engaging in a merger, we first estimate two selection equations. They provide useful information in their own right regarding the prevalence and type of mergers we observe in our sample. Since these characteristics may differ for acquirers and targets, we estimate the selection equations separately for both types of firms. The exact definitions of the two samples of potential acquirers and targets is provided below. For each of the two options, $x = \{\text{acquirer, target}\}$, the following treatment model is estimated:

$$M_{it}^{x} = \sum\nolimits_{a} \gamma_a \, X_{it-p}^{a} + \sum\nolimits_{b} \gamma_b \, X_{kt-p}^{b} + \gamma_s + \gamma_t + \varepsilon_{it} \tag{1}$$

The dummy variable M_{it}^{x} takes a value of one if firm *i* is an acquirer (target) between period *t*–1 and *t*. X_{it-p}^{a} is a set of firm-level variables measured at a time before the takeover, X_{kt-p}^{b} are a set of industry characteristics, and γ_s and γ_t are industry and year dummies. We assume the extreme value distribution for the error term and estimate equation (1) using a logit model.

2.3. Exact matching on discrete covariates

The three studies that evaluated the evolution of total employment for the entire merged entity, which we discussed earlier, largely ignore the endogeneity of mergers. They only include several control variables in the performance regression; e.g. Gugler and Yurtoglu (2004) specifically include the R&D to sales ratio to capture potential dependency of merger activity on technological change. We rely more explicitly on the selection-on-observables assumption to select a group of appropriate counterfactuals from the full set of all non-merging firm-pairs. If employment growth is independent of takeover activity once we condition on a set of

covariates, our treatment effects estimator obtains a causal estimate of a merger on the employment evolution (Imbens, 2004; Imbens and Wooldridge, 2009).

Naturally, this is a big assumption and its plausibility depends on the richness of covariates available in the dataset. Our matching variables are chosen to capture the diversity of mergers as well as possible. They include the detailed industry of the acquirer and the target (166 industries) which controls for different types of mergers across combinations of industries. They include the size and pre-merger growth performance of both target and acquirer, being a major determinant of both takeover decisions and employment growth. Finally, they include two variables that capture the corporate structure of both firms. As we match exactly on the combination of these variables, we allow for millions of possible combinations that can represent various determinants of merger decisions and employment growth.

Moreover, an advantage of using employment growth as dependent variable is the implicit conditioning on a firm-fixed effect. Any difference between merging and control firms that is constant over time is controlled for. Matching exactly on covariates, as we do, is also much more flexible than simply including covariates in the performance regression which only controls for differences in mean outcomes between treated and controls along each dimension separately. If one is not willing to assume that treatment is exogenous, not even conditionally, our estimates have a clear interpretation. By constructing a valid benchmark, a pair of non-merging firms observationally equivalent to the merging firms, our estimates capture the performance difference explained jointly by the unobservable that leads to the merger and the subsequent effect of the merger.

While much of the literature uses the propensity score to identify close matches (Lehto and Böckerman, 2008; Bandick and Görg, 2010), we match firm-pairs exactly on a set of discrete pre-merger characteristics of the acquirer and the target. It eliminates entirely all imbalances in observables, i.e. differences between the treated and control groups, and fully exploits the limited the number of explanatory variables in our dataset. Exact matching is feasible because we observe a very large number of potential counterfactuals and can thus define cells based on the interactions of all covariates. It allows very flexibly for an important role of combinations of characteristics of targets and acquirers. Remaining differences between observations are all within very narrowly defined cells, for firms that share the same values for all covariates. In

contrast, propensity score matching is preferred when the number of covariates is relatively large and many variables are continuous.

The estimation proceeds in two steps. First, the sample of takeovers and the universe of potential control firm-pairs is partitioned into mutually exclusive cells defined by the interactions of nine discrete covariates: the year and, for both firms, the industry, a dummy for firms affiliated with a company group, and discretized versions (by quartile) of pre-merger firm size and growth. The interaction of these nine matching variables generate 123,450,880 possible cells, most of which are empty. Only (observations in) cells that contain at least one takeover and one control firm-pair are retained, leaving 2171 cells.[10] To keep the number of counterfactual pairs per cell to a manageable number, we limit the number of firms that match the target characteristics to 150 for each cell (randomly selected).[11] Each cell contains between 1 and 5 takeovers (on average 1.2) and between 1 and 9200 counterfactual pairs.

In a second step, the treatment effect is calculated simply as an average over all retained cells of the difference in employment growth of firms involved in a takeover, the treated observations, and the average employment growth for the control firm-pairs in the same cell, which represents an estimate of the potential outcome in the absence of treatment, i.e. if the firms would not have merged.[12] In practice, we estimate the second-stage outcome model using the following regression:

$$g_{jt} = \alpha + \beta M_{jt} + \varepsilon_{jt}, \tag{2}$$

where g_{jt} is the firm-level employment growth rate, and the dummy variable M_{jt} takes a value of one if pair j is a takeover observation and zero if it is a control firm-pair. β represents the percentage point difference between the mean employment growth rate of the merged firms j and the outcome if they would not have been involved in a takeover.

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[10] This eliminates 12 percent of all observed takeovers.

[11] This only affects industries with many small firms such as construction, retail or restaurants. The number of firms that match the acquirer characteristics never exceeds 150 per cell. Observations with outliers in growth between *t*-1 and *t* are also excluded (growth rates smaller than -50% or larger than +50%).

[12] Given the large number of control firms, our exact matching approach is identical to nearest neighbor matching using the propensity score for a set of discrete covariates. It is also identical to a regression adjustment estimator with fully interacted discrete covariates (Imbens, 2004). Our strategy is similar to stratified matching (Anderson, Kish and Cornell, 1980) and coarsened exact matching (Iacus, King and Porro, 2012) which share the advantage of exact matching that bias is reduced and precision gained as the number of subclasses is increased.

As there are many more control than treated observations, we need to use weights to obtain the correct difference in average growth rates. The weights w_{jt}^{c} assigned to an observation *jt* in cell *c*, are equal to:

$$w_{jt}^{c} = \begin{cases} 1 & if\ M_{jt} = 1 \\ \dfrac{\sum_{jt \in c} M_{jt}}{\sum_{jt \in c}(1 - M_{jt})} & if\ M_{jt} = 0. \end{cases} \tag{3}$$

In a cell with N_c control observations and only a single takeover, which is the most common situation, all controls receive a weight of $1/N_c$. As observations within cells can contain similar firms, we report cluster-robust standard errors. This relaxes the independence assumption and requires only that the residuals of the performance equation are distributed independently across the cells.

The regression model (2) is used to estimate the impact of takeovers on employment growth between the last observation prior to and the first observation after the transaction (*t*-1 to *t*). Since labor force adjustments can take time or takeovers can have a persistent impact on employment growth, we extend the dependent variables to growth rates up to the 3-years after the takeover. The post-merger impact will be estimated both as year-on-year employment changes, as well as cumulated changes over the entire post-merger periods. The first provide information on the dynamic adjustment paths conditional on surviving, while the latter give insight in the long-term employment gains or losses following a takeover.

Following Davis, Haltiwanger and Schuh (1996), we calculate growth rates as employment changes relative to the average of employment at the beginning and end of the period considered.[13] These growth rates range from -2 for exits to +2 for entrants, show job creation and destruction symmetrically, and are bounded away from infinity. Divestitures and

[13] Denoting employment of observation *j* in year *t* as E_{jt}, the *k*-year growth rate equals $g_{jt} = \left(E_{jt} - E_{jt-k}\right)/\bar{E}_{jt}$, with $\bar{E}_{jt} = \left(E_{jt} + E_{jt-k}\right)/2$. These growth rates are close to the more commonly used logarithmic growth rates $g_{jt} = \ln\left(E_{jt}/E_{jt-k}\right)$, especially for small changes. An advantage is that we do not have to restrict the analysis to surviving firms. As our sample includes many small firms, we want to allow for the possibility of exit and associated employment loss as an outcome in the post-merger years. As mentioned, we use as dependent variables both employment growth over *n*-year periods, which calculates changes from *t*–1 to *t*+*n* for *n*={1,2,3} for all observations, and year-on-year employment growth, which calculates changes from *t*+*n*–1 to *t*+*n* for *n*={1,2,3} and conditions on survival to *t*+*n*–1.

additional changes in the firm structure are accounted for by an employment imputation procedure discussed in Section 4.

The exact matching with counterfactual pairs of firms for each takeover allows for a flexible way to introduce heterogeneous employment effects of takeovers, depending on the joint features of the acquiring and the target firm. To allow for differences in effect by merger-type, we define a various subsets of mergers using combined acquirer and target firm characteristics. We then evaluate whether the estimated takeover effect differs significantly for different subsets by introducing in equation (2) a dummy variable S_{jt} for the subset, as well as its interaction with the takeover dummy:

$$g_{jt} = \alpha + \beta M_{jt} + \gamma S_{jt} + \delta M_{jt} S_{jt} + \varepsilon_{jt}. \tag{4}$$

The coefficient of interest is now δ, which measures the difference in the takeover effect on employment growth for the mergers in the subset relative to the average for all other mergers.

3. Data

The analysis is based on the register of Belgian employers maintained by the National Social Security Office. It covers all private firms with at least one employee in the period from 2003 to 2012. Firm employment is measured as the number of employees on June 30 of each year.[14] Information on the control structure of firms—i.e., whether they are part of a domestic or foreign enterprise group—is taken from a dataset provided by Statistics Belgium. An overview of all variables and their exact construction is provided in Table A.1 in the Appendix.

We identify takeovers or mergers between two or more firms between 2005 and 2012 using two methods, which are discussed in detail in the next section. It leaves us with an unbalanced panel of firms that includes at least two years of information prior to each merger in order to observe control variables.

Some takeovers, namely those involving temporary agencies and firms in highly subsidized sectors, are excluded to avoid measurement error due to firms with incomparable growth

[14] In an average year, the sample includes 178,000 firms and 2,070,000 employees.

patterns.[15] As noted before, the few takeovers by very young or small acquirers are dropped and we also exclude takeovers where the target is very small compared to the acquirer. These events do not correspond to substantial workforce integrations, which is the focus of our study, and they do not satisfy the common support condition as they have an almost zero probability of occurring. Remaining takeovers in our sample satisfy the following conditions: The acquirer has at least 10 employees and is at least 4 years old in the year before the transaction (t-1); the target has at least 2 employees and is at least 1 year old in t-1; the target represents at least 1 percent of employment of the combined entity; the merged entity survives in t. Of all firms not involved in a takeover, firm-year observations that meet these same conditions are used to construct potential counterfactuals.[16]

We control carefully for other changes in the firm structure that may occur before or after the takeover. Takeovers can be accompanied by divestitures of parts of the firm in the year of the transaction or in the post-merger period. Moreover, firms may engage in another merger, split up, or disappear from the dataset because they change identification number. Statistics in Table A.2 show that firms involved in a takeover have a much higher probability to be involved in an additional restructuring than other firms. Studies that do not control for such events are likely to measure employment levels in the post-merger period with error, which will bias estimates of takeover effects on employment growth.[17] We control for ID changes and changes in the firm structure that occur before or after the takeover period using three record linking methods: employee-flow record linking, probabilistic matching, and relying on supplementary data sources. They allow us to reconstruct consistent employment histories of firms involved in a takeover three years before and three years after the transaction.[18]

The source data contains information on the firms' industry at the NACE 4-digit level. The selection equations that we estimate include industry dummies or time-varying variables at various levels of aggregation. Knowledge intensive industries are identified using the Eurostat

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[15] Temporary agencies exhibit continuous reshuffling of legal entities within enterprise groups; firms in highly subsidized sectors experience employment growth that strongly depends on changes in policy measures.

[16] A firm may be included in a control firm-pair in each year it satisfies these conditions. Note that potential acquirers are a subset of potential targets.

[17] Gugler and Yurtoglu (2004) partly address this problem by introducing a dummy for divestiture activity.

[18] This process is briefly described in the Appendix and documented in greater detail in Geurts (2016) and Geurts and Van Biesebroeck (2016).

classification of Knowledge Intensive Activities and declining industries are defined as 2-digit sectors that exhibited negative output growth between *t*-3 and *t*-1. We also use a ratio of industry concentration, equal to the employment share of the four largest firms at the 3-digit level in *t*-1, and a dummy for increasing concentration if this share increases from *t*-3 to *t*. Table A.1 in the Appendix provides more detail on the exact construction of these variables.

4. Takeover activity

4.1. Frequency of takeover activity

Most previous studies focus on mergers and acquisitions by listed or large firms which results in relatively small samples even for large countries and over extended periods. For example, Conyon et al. (2002) use a sample of 277 mergers and acquisitions for the UK over 21 years (1975-1996). Gugler and Yurtoglu (2004) study 646 mergers and acquisitions for the whole of the U.S. and Europe over 11 years (1987-1998).

A few studies use a different approach to identify a comprehensive set of mergers for a particular jurisdiction. Lehto and Böckerman (2008) for Finland and Burghardt and Helm (2015) for Switzerland construct a sample that covers the universe of transfers of control for active establishments in the respective countries. The first study relies on reports by a trade magazine and records all instances where a transaction changes which firm owns at least 50% of an establishment. It excludes targets or acquirers with annual turnover below (approximately) €500,000 and separately identifies takeovers by foreign firms with no prior presence in Finland. In total, 7923 establishments experienced an ownership change over a 15-year period (1989-2013), or an average of 566 per year. Takeovers are pro-cyclical and their frequency is greatly influenced by industry restructurings that can lead to hundreds of establishments changing ownership in a single year.

The second study identifies all establishments where the identification number of the controlling firm changes for any reason between the 2001 and 2005 business censuses. It drops firms that only own a single establishment in 2005 in order to exclude simple ownership changes. Comparing takeover frequency with the complete Swiss business census shows that of the 305,410 active establishments in 2001 that survived to 2005, 5489 (1.54%) changed

ownership over those 4 years. This rate was almost twice as high for service establishments (1.64%) as for manufacturing (0.89%).

Brown and Medoff (1988) start from the universe of employers that report to the Michigan Unemployment Insurance system. In the payroll records, they observe when employers with different firm identifiers integrate. In total they identify 2829 mergers or acquisitions that involve at least two firms over a 6.5 year period. They do not report enough summary statistics to calculate the likelihood a firm is involved in a transaction, but they mention that the entire sample counts more than 200,000 firms. A notable finding is that the employment effects of a takeover differ by type. In only 15% of the cases do the firms integrate their two workforces, mere transfers of assets (control) are much more common. Ownership changes that only lead to a transfer of assets tend to be associated with employment reductions, while instances where firms integrate their workforces on average lead to employment expansions.

Given our interest in the role of mergers and takeovers in the overall growth process, we use a procedure that focuses on firm integration. In our sample, a takeover is defined as the integration of two previously independent Belgian employer firms into a single legal unit.[19] We identify them by relying on two sources of information.

The first source is a dataset compiled by Statistics Belgium based on all official mergers and acquisition approved by the Commercial Court. It includes share deals between companies where the buyer becomes the owner of the other legal entity and acquires the target's shares and assets as well as all existing liabilities and debts.[20]

The second source is based on employee-flow linkages between firms using a linked employer-employee dataset (Geurts 2016; Geurts and Van Biesebroeck, 2016). A takeover is defined as an event where an existing company absorbs the workforce of another firm and the latter is dissolved after the transaction. The dissolved firm is defined as the target and the firm that continues as the acquirer. A merger is identified as two firms that are dissolved and merge

[19] Independency is based on the official firm identification number which corresponds to separate firms under Belgian law. Before the merger, each firm pays its own social security contributions, corporate taxes, and fills out individual annual accounts. After the merger, these obligations are fulfilled by the joint entity.

[20] Not all takeovers are subject to a Commercial Court procedure. Asset deals, mergers between firms owned by the same corporation, and buy and sell operations can be executed without approval by the Commercial Court.

their workforces into a newly created firm, represented by a new firm identifier.[21] In such case, we label the largest firm as the acquirer. Our method only picks up events where the workforce reallocation between the two firms includes at least 5 employees.

The vast majority of observations in our sample are takeovers, which means in practice that no new firm identifier is created. Plain mergers represent less than 3 percent of our sample. In line with previous studies, we do not distinguish between 'takeovers' and 'mergers' and use the terms interchangeably. When several firms are taken over in the same year, the transactions are collapsed into a single event. Takeovers in different years are included as separate events.

Using these two sources that encompass merger activity irrespective of size and company type or shareholder structure, we find that takeover activity is a much more dynamic and frequent process than one would expect based on most studies of mergers. Even for the relatively small Belgian economy, we identify over a 7-year period a comprehensive set of 2601 domestic takeovers, or an average of 372 takeovers each year, that involve 3400 target firms. They involve both small and large firms and affect an important share of employment.

[Figure 1 about here]

Figure 1 shows the population and employment coverage of acquirers and targets involved in these takeovers. Combined they represent 0.74 of active firms in a given year, targets make up a somewhat higher share than acquirers (0.42 versus 0.32 percent of all firms), as multiple firms may be acquired in a single takeover. Because takeover activity is more likely among larger firms, firms involved in takeovers account for an important share of employment. In an average year, more than 4 percent of all employees in the Belgian private sector work for a company that is involved in a takeover that year: 3.5 percent are employed by an acquiring firm and 0.8 percent by relatively smaller target firms. Over an average 5-year period, firms that engage in takeover activity cover 17 percent of total private employment. The two sources are complementary for the identification of takeovers. The Commercial Court files identify 58 percent of all takeovers in the sample, but most of these are also picked up by the employee-

[21] More specifically, a takeover corresponds to an event where at least 50 percent of the individual employees of the dissolved firm is transferred to the incumbent. Similarly, a merger corresponds to the transfer of at least 50 percent of the individual employees of two dissolved firms into a new legal entity. Most takeovers and mergers in the sample correspond to transfers of close to 100 percent of the workforces into the combined entity.

flow method, which covers 85 percent of the sample. 42 percent of takeovers are only identified by the employee-flow method and a small share, including mainly smaller firms, is only found in the Commercial Court files.

[Figure 2 about here]

Takeover activity varies strongly by sector as shown in Figure 2. Firms in Energy are most likely to engage in a takeover (1.8% per year), followed by firms in Transport, Manufacturing and Business services. In terms of employment, employees in Energy and Business services are most likely to be affected (ca. 6%), followed by Manufacturing (5%). Takeover activity in these sectors is relatively more concentrated among larger firms. The statistics in panel (b) provide more information about the sample composition. More takeovers are by firms in Trade than in any other sector, but the absolute number of firms in a takeover (as targets or acquirers) is large as well in Business services and Manufacturing. Together, these three broad sectors make up 71 percent of the sample.

4.2. Characteristics of acquirer and target firms

Table 1 summarizes pre-merger characteristics of acquirers and targets, and compares them to the more than 800,000 firm-year observations of non-merging firms that could serve as valid counterfactuals. The three subsets differ widely on a set of basic features, highlighting the importance of the matching approach. Acquirers employ on average 189 employees in the year before the merger. They are 6 times larger than target firms, and more than 10 times larger than the average non-merging firms. Size distributions are strongly right-skewed, as can be seen from the much smaller median sizes of 45, 12 and 4 employees respectively. The median sizes further illustrate why it is vital not to focus only on takeovers by large firms. Even the majority of acquiring firms are relatively small.

[Table 1 about here]

Pre-merger performance differs greatly as well. The average employment growth of acquirers in the two-year period before the merger is 4.6 percent, compared to 8.9 percent for targets. This difference mostly reflects the age conditions we imposed on the two samples: acquirers are at least 4 years old and targets at least one year old. If targets that enter in *t*-2 are

excluded, their average growth rate turns negative (-4.5 percent).[22] Growth rates of non-merging firms are much higher, at 22.7 percent overall, or 9.5 percent if entrants are similarly excluded. Their high growth rates is again partly explained by their younger age composition: more than 18 percent are 5 years or younger, while this share is only 1.2 percent among acquirers and 5.5 percent among target firms. The averages mask wide underlying variation, as can be seen from the large standard deviations. Differences across sectors explain part of this variation, but standard deviations are also large within sectors.

Another difference between the subsamples is that firms involved in a takeover are more likely to have been involved in another firm restructuring before the merger. This can be another merger, a split-up, ownership change or another form of restructuring involving multiple firms. More than 20 percent of acquirers and 10 percent of targets have been involved in a restructuring in the 5-year period before the merger. The corresponding share for non-merging firms is only 6 percent. Finally, firms involved in a takeover are much more likely to be part of a larger company group than non-merging firms, and they engage more often in foreign direct investment. More than half of the acquirers are part of an enterprise group and 11.5 percent were engaged in (inward or outward) FDI in the period before the merger. The shares are somewhat lower for target firms and minor for non-merging firms.

As counterfactuals for each of the takeovers, our matching procedure will select pairs from the large set of non-merging firms that are similar to the acquirer and target firms. In Table 2 we show some patterns that illustrate the importance of accounting for the features of each firm on its own as well as taking into account their combined characteristics. Results in panel (a) show how the average size of the target firm increases almost as strongly across the size quartiles of acquirers as the acquirers' own size, and vice versa for the size quartiles of targets. Even though most targets are small enough to be feasible takeover targets for a large majority of acquirers—e.g. almost 90 percent of targets are smaller than the median acquirer and the 75th percentile in size of targets approximately equals the 25th percentile for acquirers—there is a strong association between the two firms' relative sizes.

[Table 2 about here]

[22] According to our definition, growth rates of entrants equal 200 percent.

Panel (b) reports that a similar type of assortative matching takes place based on pre-merger growth rates. The relationship is almost as monotonic as for size in panel (a), but with one exception. Acquirers with growth rates in the bottom quartile, which on average are strongly negative, tend to take over targets that have an average growth rate close to the overall mean. Similarly, targets that show the slowest growth, which is even more negative on average, tend to be taken over by acquirers with average growth rates. Our exact matching procedure based on the interaction of characteristics allows flexibly for such systematic patterns.

We next describe estimates of selection equation (1). The objective is both to provide insights into which type of firms enter into mergers, as well as to illustrate the predictive power of the variables that we use in the exact matching. Columns (1) and (2) of Table 3 show results for the acquirer dummy as dependent variable and columns (3) and 4) show results for targets.[23]

[Table 3 about here]

The linear and quadratic size variables imply that the probability of being an acquirer or target increases concavely with firm size (measured by employment). The more negative squared term for targets indicates that the positive effect of size decreases more rapidly for them. Lagged growth is negatively correlated with takeover activity. Firms that increase employment more rapidly are less likely to be an acquirer and especially less likely to be a takeover target. Being part of an enterprise group significantly increases the probability of engaging in a takeover, while the coefficient on the FDI dummy is estimated much less precisely and also less robustly. One reason is that it is highly correlated with the enterprise group dummy. If the FDI dummy is included on its own, the point estimate is strongly positive for both acquirers and targets. When included in addition to the enterprise group dummy, it is estimated much smaller for targets and even switches sign for acquirers.

The results in columns (1) and (3) include broad sector and year fixed effects, but also a number of time-varying industry characteristics that are measured at a more detailed level. They show that firms in declining industries are less likely to be the target of an acquisition, while this feature has no significant effect on being an acquirer. In contrast, firms in knowledge

[23] Note that the number of observations differs for the two regressions because they are either based on the subsample of firm-year observations that satisfy the preconditions of an acquirer, or the preconditions of a target.

intensive sectors are more likely to engage in takeovers and this positive effect is especially pronounced for targets. Companies in highly concentrated industries are significantly less likely to acquire other firms and this tendency is further diminished if the industry has recently become more concentrated. At the same time, however, there is some evidence for merger waves as an increasing level of industry concentration is strongly associated with firms in an industry being taken over, and a high existing level of concentration does not deter this. The opposing coefficients for acquirers and targets suggests that the two sides of these transactions often come from different industries.

For the results in columns (2) and (4), the broad industry-fixed effects and the detailed industry variables that only varied slightly over time are replaced by a full set of 166 industry-fixed effects at the NACE 3-digit level. Compared to the earlier results, the absolute magnitudes of most coefficient estimates decline slightly, but changes are minor. All firm-level coefficients remain highly significant.

In Table A.3 in the Appendix, we use the more flexible results with detailed industry-fixed effects to verify whether results are similar for acquirers and targets identified using either of the two data sources used to identify takeovers. We first show estimates for takeovers that are legally obliged to obtain approval of the Commercial Court, which produces a sample of takeovers more similar to Lehto and Böckerman (2008) and Burghardt and Helm (2015). In the other columns we presents results for takeovers that are only picked up by the employee-flow method. The results in both subsamples are very similar, suggesting that the less conventional employee-flow method picks up reorganizations between firms that do not fundamentally differ from officially registered takeovers. Two differences have an obvious explanation. First, the larger size coefficient for targets in column (4) is a direct result of the employee-flow method which by construction does not identify takeovers of very small firms (i.e. with fewer than 5 employees). Second, the larger coefficient for the enterprise group dummies in columns (1) and (3) suggest that firms belonging to a larger corporation are likely to be subject to more stringent legal obligations and therefore more likely to appear in the Commercial Court files.

5. Employment effects of takeovers

5.1. Pre- and post-matching statistics

The earlier results highlighted the importance of constructing a valid control group. Firms in takeovers differ notably from non-merging firms and even acquirers differ from targets, requiring separate control groups for the two subsets. We also found substantial variation in the features of the partner that acquirers choose to ally with, which we account for by selecting as counterfactuals pairs of firms that jointly match the characteristics of both partners.

More specifically, the nine (discrete) matching variables that we use are the base year of the takeover period (*t*-1); the NACE 3-digit industry codes of the acquirer and the target; the size quartile of the acquirer in *t*-1, defined within each industry-year; the lagged growth quartiles of the acquirer and the target between *t*-3 and *t*-1 (with an additional category for targets that enter in *t*-2), also defined within industry-years; dummies indicating whether the acquirer and target are part of a company group; and finally, a dummy indicating whether the employment share of the target in the combined entity in *t*-1 is above the median share for the full sample (which equals 0.25).

Table 4 illustrates the result of the exact matching procedure. It shows side-by-side the averages for the 9 (numbered) matching variables, on the left for the full sample of takeovers and potential matches, and on the right for the takeovers that remain in the final sample and the matched firm-pairs. The first rows show that the number of takeovers is reduced after matching in order to satisfy the common support assumption. While the sample contains about 165,000 observations of non-merging firms that satisfy the preconditions of an acquirer in *t*-1, and 725,000 that satisfy the preconditions of a target, the sample of paired firms after matching includes more than 1.7 million observations. The statistics for these pairs, as reported in the other rows of Table 5, are based on weighted averages with the weights defined in equation (3).

[Table 4 about here]

Results in the third and last columns, labeled |A-B| and |C-D|, show that differences between firms in takeovers and the control group are strongly reduced after matching. The exact matching procedure necessarily leads to the two samples being perfectly balanced for all discrete variables, i.e. by 3-digit sector and year (rows 1,2 and 1,3), as well as by the share of

firms that are part of an enterprise group (rows 4 and 5). For the last four variables we match exactly on the quartile, but report the averages for the continuous size and growth variables.[24] Differences in the means and medians of firm size (rows 6 and 7) and growth rates (rows 8 and 9) are strongly reduced after matching, but do not disappear entirely. The strong reduction in the absolute size difference between targets and controls is an indirect effect, as we only match on the relative size of the target in the merged entity.

As important as the balancing of takeovers and counterfactuals with respect to the characteristics of acquirers and targets individually, is that the matching procedure imposes similarity between the two samples regarding the joint characteristics of both partners. Since no equivalent for pairs of firms exists in the pre-matching control group, we cannot illustrate this gain in a similar way.

5.2. Average effect of takeovers on firm employment growth

Table 5 presents the results for the impact of takeovers on firm-level employment growth until the third year after the transaction. In panel (a) we report the effects on year-on-year employment growth and in panel (b) the effects on growth rates calculated over the entire *n*-year post-merger period. The coefficients measure the average treatment effects on the treated, estimated using outcome model (2) and comparing the outcome for the takeover to the average outcome for control firm-pairs that exactly match the acquirer and the target on a set of characteristics.

[Table 5 about here]

The first column of panel (a) shows that takeovers have a small but significantly negative impact on the employment of the combined entity immediately following the merger. Employment growth is 2.3 percentage points lower than it would have been without the merger. Results in the next columns indicate that the adverse effect persists for several years. Growth continues to be approximately 2 percentage points lower than for the benchmark firms in the

[24] It means that for a takeover that involves an acquirer in the first size-quartile and a target in the second size-quartile, we form all possible pairs of non-merging firms from the same industry in the same year, that fall in the exact same size quartiles. While the size-quartiles will be identical for the takeovers and controls, as is also the case for the five discrete variables listed first, the exact firm sizes will still vary somewhat.

three years after the transaction, and differences remain highly significant. The employment contraction only diminishes by the fourth year after the transaction.

Panel (b) shows the impact on employment over the entire post-merger period, i.e. from the pre-merger employment level in *t*-1 to the *n*th year after the transaction. These estimates do not condition anymore on surviving in the preceding period, and confirm the persistent and strongly negative impact of takeover activity on firm employment growth. By the first full year after the merger, employment relative to the pre-merger level is reduced by more than 4 percent. Measured over the 3-year post-merger period, the cumulative adverse effect amounts to more than 8 percentage points lower employment growth than experienced by non-merging firm-pairs. As a robustness check we varied the number of control observations or conditioned throughout on survival until *t*+3, but the point estimates, which are reported in Table A.4 in the Appendix, are remarkably invariant to these changes.

Finally, in panel (c) we report the effects of takeovers on the change in growth rates after the merger, which confirm the adverse effect of takeovers on the employment evolution. While the results for employment growth in panels (a) and (b) control for a firm-fixed effects in the employment level, the effects on the growth acceleration even control for a firm-fixed component in employment growth. The first column compares employment growth in the year of the takeover with the growth rate in the year before the merger. The second column presents results based on a comparison of two-year growth rates. The negative coefficients of -0.8 and -3.0 indicate that employment growth of firms involved in a takeover significantly slows down.

Our exact matching approach requires all covariates to be categorical and we discretized four of the matching variables: the absolute size of the acquirer, the relative size of the target, and the pre-merger growth rates of both firms. The summary statistics in Table 4 show that it leaves some variation in the underlying continuous variables within the detailed cells as defined by the interaction of all nine discrete covariates. Other treatment effects estimators allow for continuous variables and, for example, match on the propensity score. The possible gain in matching accuracy comes at a cost of being less flexible in the interaction between acquirer and target characteristics.

We can add an additional step in our algorithm and instead of estimating the average treatment effect as the difference in simple within-cell averages, we can use a treatment effects estimator that controls for the remaining heterogeneity in the continuous variables. But the

gain in matching precision comes at a price. For the common support condition to hold within cells, we cannot use the same industry detail, defined by the combined NACE 3-digit codes of the acquirer and the target. As observations that closely match on pre-merger size and growth can often not be found in these very detailed cells (166*166 industries), it would drop many takeovers from the analysis. We therefore have to use coarser industry definitions, i.e. the NACE 2-digit level for the acquirer and the broad sector affiliation of the target.[25] We include the three other matching variables (year of observation and dummies for enterprise group) as before.

In Table A.5 in the Appendix we show results using propensity score matching and inverse-probability-weighted regression-adjustment that use the continuous values for four of the matching variables. To ease the computational burden, the estimates are based on a subsample with exactly 30 matches per takeover and panel (a) repeats the baseline results for this subsample using exact matching. The coefficient estimates for the two alternative estimators in panels (b) and (c) show slightly less pronounced effects of takeover activity on post-merger employment growth. The difference between the estimates are minor—effects are reduced by one tenth, on average, and the largest reduction is by one fifth—and the standard errors are highly similar, illustrating the robustness of our results.

5.3. Differential effects by type of firm

The average effects of takeovers on employment growth that we estimated above could mask large differences between takeovers. We now investigate whether differences in post-merger employment growth are systematically related to observable characteristics of acquirers or target firms.

Table 6 shows such differential impacts by splitting the sample approximately in half using individual firm or industry characteristics. Each coefficient is estimated using a separate regression like equation (4), where the subset dummy is defined using a single characteristic. The table reports the δ coefficient on the interaction between the takeover and subset dummies. The top panel uses firm-level characteristics that are binary versions of the matching variables,

[25] The NACE 2-digit level and the broad sector affiliation comprises 76 and 9 categories, respectively. As the estimation for the 3- and 4-period growth rates are based on fewer takeovers, only the broad sector affiliation of both partners can be used there.

as well as a dummies for foreign ownership. The lower panel uses industry features and also reports the few instances where the effect in a particular takeover year was systematically different from the average.

[Table 6 about here]

No variable has a significant effect on employment growth in all four periods. The large standard errors of most coefficients suggest substantial variation within subsets, which may be explained by other features of the takeovers or may simply be idiosyncratic. Of all the firm-level characteristics, only the relative size of the target leads to a significantly different effect in two of the four periods. Employment contractions in the 2- and 4-year periods after the transaction are less pronounced when relatively small firms are acquired. It is only natural that the potential for workforce rationalizations in the combined entity is more limited when a firm takes over a much smaller target. Pre-merger performance has a significant and positive effect on the merger outcome as well, but only in the period of the transaction itself. The coefficients remain positive in all post-merger periods, but are not longer statistically significant.

Overall, we find that firm-level features do not lead to systematically different post-merger outcomes. Most remarkable are the small differences and entirely insignificant coefficient estimates for the vertical merger dummy, which takes a value of one if the two firms are not in the same NACE 3-digit industry. Several authors have discussed the relevance of distinguishing between horizontal and vertical mergers (Lafontaine and Slade, 2007) and empirical studies based on small samples of takeovers by large or listed firms have highlighted differential impacts, although going in either direction (see Conyon et al. 2002 and Gugler et al. 2003). Below, we show that the industry relatedness does play a role in post-merger outcomes, but only when other characteristics of the acquirer and target are taken into account.

Results in the lower panel of Table 6 indicate that most industry characteristics of the merging firms do not explain differences in post-merger outcomes either. We find insignificant coefficients for takeovers with an acquirer or a target operating in manufacturing, in an industry with declining output growth in the year before the merger, in an industry with a high or increasing level of concentration, or in a knowledge-intensive industry. The large standard errors again suggest substantial variation among takeovers within these types of industries. The only feature that does have a significant effect on post-merger employment growth is a

Trade or services affiliation. Takeovers with an acquirer (a target) in this sector lead to relatively more positive employment outcomes from the first (second) post-merger period onwards.[26]

5.4. Differential effects by type of takeover

Our matching strategy is based on a paired perspective: counterfactual pairs of firms have been selected on the basis of the joint similarity with both the acquirer and the target of the observed takeovers. The decision to expand or contract the workforce following the transaction could also depend on the joint characteristics of both partners. While the individual firm or industry characteristics of the two merging firms did not predict differences in post-merger employment outcomes, we now show that outcomes are often significantly different if we look at acquirer and target characteristics in combination. The joint features of both partners implicitly define different types of mergers or takeovers.

A first way of showing this is to estimate separate effects for a large number of detailed subsets. We define 2^7 or 128 non-overlapping subsets using the full interaction of seven dummy variables that correspond to binary versions of the matching variables.[27] They are dummies for vertical mergers, acquirers in the largest size quartile, acquirers and targets with above average pre-merger growth, acquirers and targets that are part of a company group, and a target share in the combined entity larger than 25 percent. We estimate a separate employment effect for each subset relative to all other takeovers using separate regressions of specification (4). We only report the coefficients for the 71 subsets with at least 10 takeovers.

[Figure 3 about here]

Figure 3 shows the distribution over all subsets of the estimated takeover effects for the two-period employment growth rate (from *t*-1 to *t*+1). The horizontal axis of the histogram shows the total effects $(\beta + \delta)$ for each subset relative to the appropriate control group. Since each subset includes only a small number of takeovers, β approximately equals the average takeover effect in the sample, which equals -4.6 percent and is indicated by the vertical line. The black

[26] Note however that the overall effect $(\beta + \delta)$ is still negative and statistically significant.

[27] Of the nine matching variables, the industry codes of the acquirer and the target are now captured by a single vertical merger dummy and the year of observation is not included to define takeover types.

areas of the histogram indicate subsets for which the takeover effect differs significantly from the average effect (δ significantly different from β at the 10 percent significance level).

In several cases we find a takeover effect that differs strongly from the average. In 17 percent of the subsets, the total effect on employment is even positive, while in 18 percent of the subsets, takeovers reduce employment by more than 10 percent over two years. In most cases, however, the takeover effect does not differ significantly from the mean. The reason is that most mutually exclusive subsets contain only a small number of observations, on average 28 takeovers and their controls. As a result, only in the tails of the distribution do we find subsets where the takeover effect is significantly different.[28]

A second way to illustrate that post-merger employment outcomes can depend on the combination of attributes of the acquirer and the target firm, is to zoom in on two examples for very distinct types of mergers. Lumping together some of the subsets that were shown in Figure 3, we highlight, first, that differences in outcomes can be very pronounced, and second, that the unique effect disappears when a feature of either the acquirer or the target firm is changed. Before illustrating these patterns, we briefly discuss a possible rationale behind the very negative or positive employment outcomes in those particular examples.

[Table 7 about here]

The first example looks at takeovers by acquirers that operate in industries with negative output growth in the three years before the merger. Horizontal mergers in industries with declining demand have been hypothesized to be motivated by efficiency gains through capacity rationalization (Dutz, 1989). In such a situation, a merger may allow firms to retire older, outdated equipment or technologies and combine the most promising parts of each firm with state-of-the-art technology. This is expected to raise labor productivity and lead to workforce reductions. Results in Table 5 did not show an overall more negative effect for takeovers in

[28] The three subsets with a takeover effect that is significantly more negative are all horizontal mergers between two firms with a below-average pre-merger growth, and a target that represents more than 25 percent of the combined entity (but with different values for the other three dummy variables). The three subsets where the effect is significantly more positive are also horizontal mergers, but now the merging firms are both part of an enterprise group, the acquirer is large and the target represents only a small share of the combined entity. The other four subsets in the right tale of the distribution, but with insignificant δ coefficients, are all vertical mergers, but with different values for the other characteristics.

declining industries, but we now investigate whether effects are systematically different when we additionally condition on other characteristics.

In panel (a) of Table 7, we first present results for the full sample including both horizontal and vertical mergers and takeovers with small and large target shares, again estimated by equation (4). It contains estimates for three subsets. The first subset of takeovers is defined by the combination of three features: (i) acquirers are in a declining industry, (ii) they are part of an enterprise group, and (iii) targets had above average pre-merger growth within their industry. The main takeover effects β apply to all pairs of firms not included in this subset, or more than 90 percent of takeovers. Hence, they are very close to the average for the full sample. The interaction effects δ are the differential employment impacts for the subset of interest and are estimated to be large and significantly positive in each of the four periods. The relative post-merger employment growth is much more favorable for this type of acquisitions. The difference is already 3 percentage points in the period of the transaction and grows to almost 17 percentage points over the full 4-year post-merger period from t–1 to t+3. The overall employment effect in the subset, equal to $\beta + \delta$, is positive for each period and even statistically significant over the full 4-year period.[29]

Importantly, the estimates in Table 7 for the other two subsets show that the above pattern only holds for the specific combination of acquirers in declining industries and high-growth targets. Changing the attributes of either of the merging firms has a large impact on the results. Estimates for subset 2 show that if the same type of acquirer takes over a target that exhibited below-average pre-merger growth, the pattern disappears. Employment effects of those takeovers are not significantly different from the average effect. Most point estimates of the interaction term are even negative, but they are never significant. Similarly, if we still focus on high-growth targets, but look at takeovers by acquirers from expanding industries (subset 3), employment differences are again indistinguishable from the average evolution.

[29] The $(\beta + \delta)$ total effect has a difference-in-differences interpretation, measuring the change in employment for takeovers in the subset relative to the change in employment change for the appropriate control group. The δ parameter has a triple-difference interpretation, comparing the differences in employment growth for takeovers in the subset with the employment growth for the other takeovers, normalizing both growth rates by the average rate of growth in the corresponding control group.

The results in panel (b) show that these findings are not confounded by observations where the target is relatively small compared to the acquirer. When we restrict the sample to mergers with relatively large targets only, the differences are even more pronounced. Results in panel (c), which restricts the sample to horizontal mergers only, are very similar to subset 1. In each case, the employment evolution is more positive for takeovers that involve an acquirer in a declining industry and a high-growth target, the opposite pattern as predicted by the merger theory discussed above. Even more importantly, both patterns disappear when we change one of the firms characteristics, which we illustrate with the estimates on subset 2.

Table 8 presents a second example that illustrates how a unique employment effect can depend crucially on the combination of features of the acquirer and the target. Here we look at takeovers where the acquirers are relatively small, i.e. in the first to third size quartile of their industry, and they take over a target that is active in Manufacturing or Construction. We condition throughout on acquirers that experienced below-average employment growth before the merger. Takeovers in this subset (subset 1) lead to very large post-merger employment reductions, up to 18 percentage points over the full 4-year period. In each period the effects are more than twice as large as the average effect in the sample.

[Table 8 about here]

In the other two subsets, we vary either the type of acquirer or the type of target, but hold the features of the other partner in the takeover constant. Subset 2 shows estimates for large acquirers and subset 3 for targets in Trade or Services. The estimates again show drastically different post-merger outcomes when we change an attribute of one of the merging firms. The takeover effects in the two subsets never differ significantly from the sample average, and many of the interaction effects even change sign. This finding is supportive of the theoretical prediction in Dutz (1989) if we consider manufacturing firms to be more likely to benefit from technology upgrading after a merger, but our estimates also highlight that the theory does not hold for acquirers in the top size quartile.

6. Conclusion

We evaluated the effects of takeovers or mergers on firm employment growth and obtained two novel findings. First, using a novel way to obtain a comprehensive sample of mergers

where firms integrate their workforces, we document that such takeover activity is remarkably widespread. Much of the literature focuses on takeovers by large or listed firms, which is understandable as these mergers are most likely to receive competition policy attention. However, such an approach will miss to a large extent the important role that takeover activity plays in the economy's growth process. Second, we find a persistent, negative impact on employment on average, but also a wide diversity in merger outcomes. Previous studies have evaluated differences in post-merger performance by conditioning on features of the acquirer, for example comparing takeovers by foreign and domestic firms, or the target firm. In our sample, we find little systematic heterogeneity in outcomes when we distinguish mergers along individual characteristics of either the acquirer or the target. We do, however, find such heterogeneity when we condition simultaneously on combined characteristics of both partners. Even for a specific type of acquirer, post-merger employment growth is found to depend crucially on the type of firm it acquires.

The merger literature has documented a variety of reasons why firms engage in takeovers. Realized takeovers, but also subsequent performance are likely to depend on these motivations. Expected employment effects are necessarily ambiguous if one averages over a broad sample of heterogeneous mergers and this might have contributed to the wide range of conflicting estimates in the literature. We have proposed a simple approach of exact matching to pairs of firms as a way of obtaining valid counterfactuals for the merging firms and more specifically valid counterfactuals for particular combinations of firms. Our analysis is limited by the available data which necessitated a focus on employment as performance variable. In a dataset with more extensive information on firm characteristics, the same approach could be used to evaluate the impact of mergers on other post-merger performance variables, such as profitability or output growth, as in Gugler et al. (2003). Importantly, the empirical approach that we propose pairs each takeover with a set of appropriate control firm-pairs. When additional variables are observed, it should be possible to better characterize different types of mergers, e.g. distinguish between mergers primarily aimed at increasing market power and mergers aimed at combining complementary assets, and estimate separate performance effects for either type.

Appendix

A.1 Imputation of employment levels in the case of multiple restructurings

To estimate the net effect of takeovers on firm employment growth as accurately as possible, we reconstruct consistent employment histories up to three years before and three years after the takeover year for firms that undergo other changes in firm structure, which can be another merger or takeover, or a split-up or divestiture. This can affect target or acquirer firms engaged in a takeover in the pre-takeover period, or the merged entity in the post-takeover period.

Our approach is to impute employment growth at the firm level by assuming the same growth rate for each firm involved in a restructuring event. More specifically, we first construct an aggregate employment level that combines all firms interlinked in a given year between t and t+1. Firm-level employment in $t+n$ with $n = \{1,..,3\}$ is then imputed by assuming the same growth rate for each firm involved in the event as the growth in aggregate event-level employment. The imputation method treats split-offs and consolidations symmetrically and preserves the firm size distribution in the sample. Employment is only imputed for three years after the event or up to the occurrence of a second event if this comes earlier. Beyond that, firm observations are excluded from the analysis, since correcting for multiple events involves a complex set of interlinked firms and the imputation often becomes less reliable.

We perform a similar, backward employment imputation for up to three years before a takeover if leading up to the takeover of interest either the target or acquirer firms themselves originate from an earlier firm restructuring, e.g. from a split-up, divestiture, or merger of other firm(s). More details on the methods for identifying events and imputing employment histories is provided in Geurts (2016) and Geurts and Van Biesebroeck (2016).

A.2 Robustness check using alternative sampling schemes

We have estimated the effect of takeover activity as the average of the within-cell differences between the observed outcomes of the merged firms and the average outcomes of the matched pairs. Counterfactual pairs were composed of all possible combinations two firms that matched the acquirer and target characteristics on nine characteristics (with a maximum of 150 counterfactual targets per cell). This matching procedure yields an uneven number of counterfactual pairs per cell ranging between 1 and 9200. We addressed this by using weights

for each counterfactual that corresponded to the ratio between the number of takeovers and counterfactuals in a given cell. To complement our results, we show in Table A.4 estimates based on alternative sampling schemes, were a small number of counterfactuals is randomly selected within each cell.

Panel (a) repeats our base-line results for the full sample of the takeover effect measured over *n*-year periods. In panel (b) the number of counterfactuals is reduced to a maximum of 10 times the number of takeovers per cell. The weights are adapted to this new subsample. In panel (c) we choose exactly 10 matches per takeover and drop cells with less than 10 matches. Weights are not required for these estimations. Panel (d) reports results where we choose exactly 30 matches per takeover. The results of the three panels show that the estimates are highly robust to alternative sampling schemes. Both the coefficient estimates and standard errors in all four periods differ only slightly from the base-line results.

Finally, panel (e) show estimates based on the subsample of takeovers and counterfactuals for which we have observations in all four periods. Takeovers and counterfactuals in 2010 to 2012 drop out as well as pairs including firms that exit before t+3, counterfactuals that are in an event before t+3, or takeovers that are in a second event before t+3. The takeover effect for this subsample is slightly more negative in the first three periods than it is in the full sample, but the differences with the base-line results are again very small.

A.3 Additional Tables

[Table A.1 about here]

[Table A.2 about here]

[Table A.3 about here]

[Table A.4 about here]

[Table A.5 about here]

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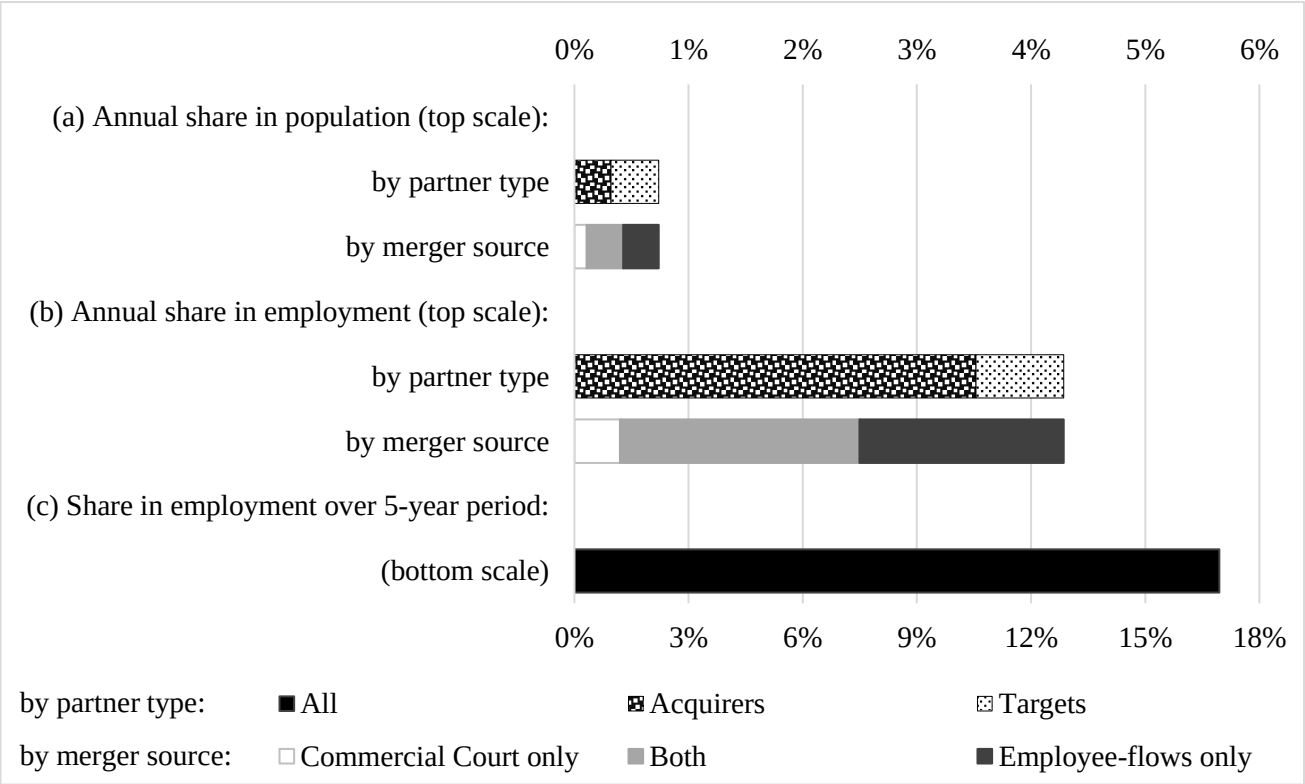
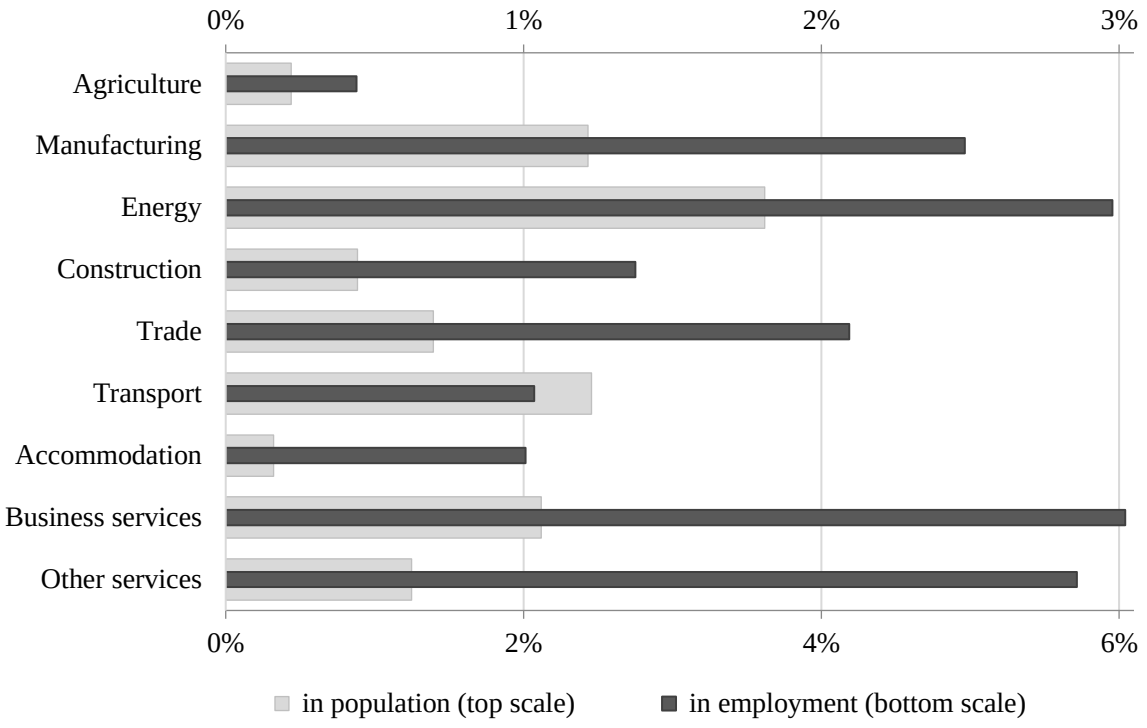
Figure 1. Frequency of takeovers in the full sample



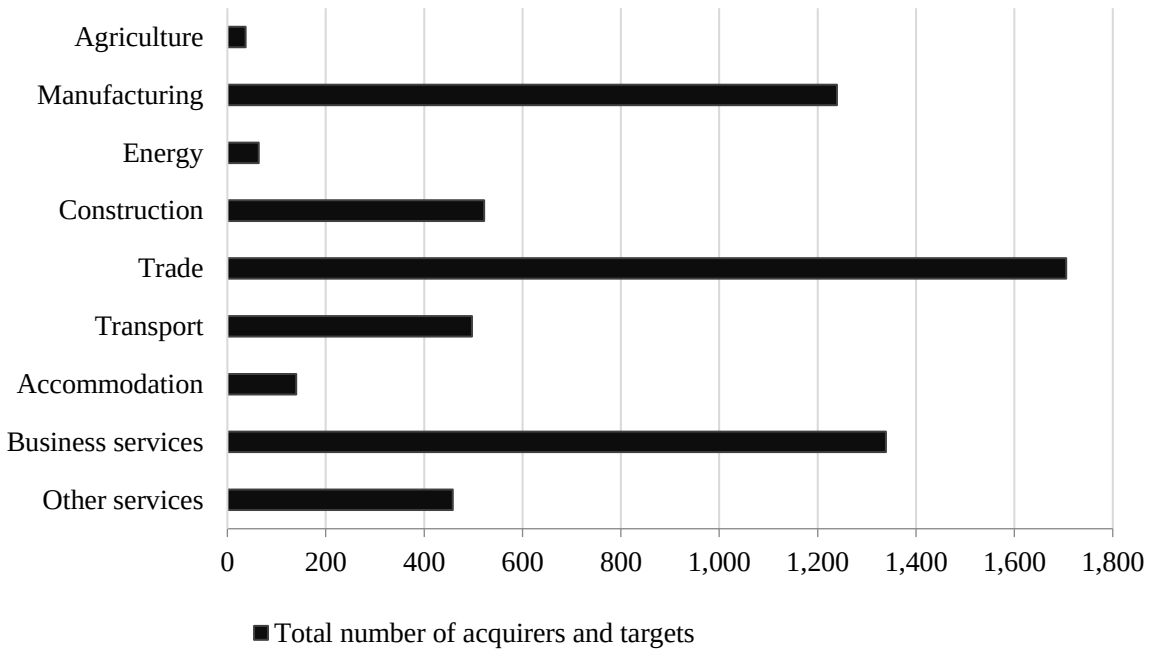
Notes: Panels (a) and (b) report average annual shares, comparing the sum of acquirers and targets to all active firms in a given year that satisfy the preconditions of a target (at least two employees and at least one year old). The share in Panel (c) is calculated as the average annual employment of all firms involved in a takeover at least once in a 5-year period, divided by the corresponding value for all active firms that satisfy the preconditions of a target.

Figure 2. Takeover frequency by sector

(a) Annual shares



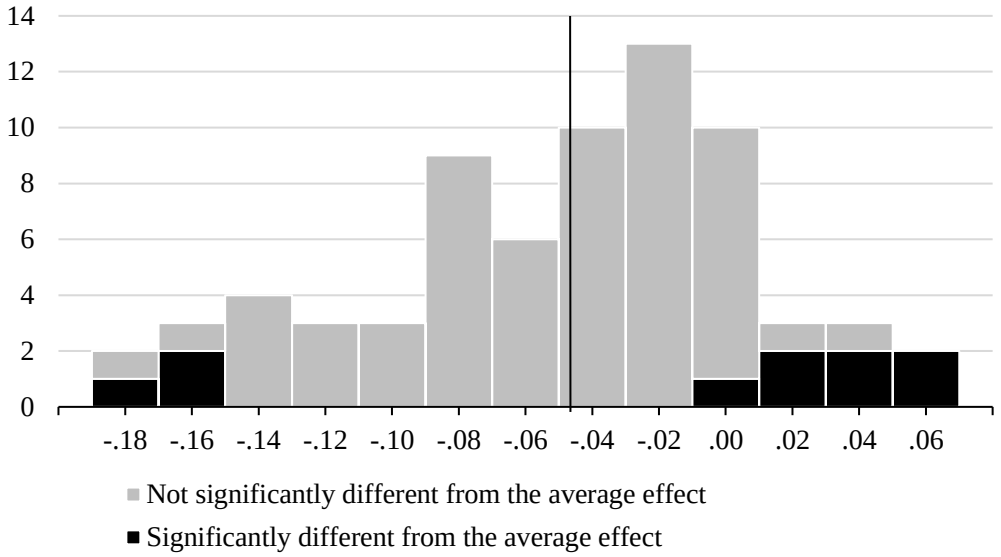
(b) Number of firms



Notes: Panel (a) reports average annual shares, based on the sum of acquirers and targets to all active firms in a given sector and year that satisfy the preconditions of a target (at least two employees and at least one year old).

Figure 3. Distribution of estimated takeover effects for detailed subsets

Dependent variable: cumulative employment growth from t-1 to t+1



Notes: Subsets are defined by the interaction of 7 dummy variables, i.e. the binary matching variables. Only estimates for subsets with at least 10 takeovers are included, which amounts to 71 subsets. The takeover effect ($\beta + \delta$) is estimated for each subset using equation (4) and the histogram is shown. The black areas of the bars indicate subsets for which the takeover effect significantly differs (at the 10 percent level) from the average effect among takeovers not in the same subset. The vertical line shows the average employment effect estimated using all takeovers.

Table 1. Characteristics of acquirers, targets and non-merging firms

	Acquirers	Targets	Non-merging firms
Number of firm-year observations	2601	3400	808,662
Size (t-1)			
Mean (st. dev.)	189 (704)	31 (103)	17 (212)
Median	45	12	4
Pre-merger growth rate (t-3 to t-1)[a]			
Mean (st. dev.)	.046 (.273)	.089 (.649)	.227 (.614)
Median	.010	.000	.000
Share of firms			
part of enterprise group (t-1 or t-2) (%)	51.7	41.5	9.6
engaged in FDI (t-2) (%)	11.5	6.7	1.1
Age distribution (t-1)[b]			
5 years old or younger (%)	1.2	5.5	18.2
more than 5 years old (%)	77.3	83.8	75.6
in event in 5-year period before takeover (%)	21.5	10.7	6.1

Notes: Statistics are based on the full sample of takeovers between 2005 and 2012 that satisfy in t-1 the preconditions of acquirers (at least 4 years old and 10 employees), targets (at least one year old and 2 employees), and target share (at least 1%). Statistics for non-merging firms are based on all firms in 2006-2012 that satisfy in t-1 the preconditions of targets.

[a] Populations of targets and non-merging firms include entrants in t-3 to t-2. Excluding entrants, growth rates are -0.045 and 0.095, respectively.

[b] Based on observations in 2008-2012.

Table 2. Combined characteristics of acquirers and targets

(a) Acquirer and target pre-merger size (t-1)

	Mean Acquirer size	Target size		Mean Target size	Acquirer size
Acquirer size quartile			Target size quartile		
Q1	15	7	Q1	4	54
Q2	31	13	Q2	8	71
Q3	77	21	Q3	17	119
Q4	632	63	Q4	75	507

(b) Acquirer and target pre-merger growth (t-3 to t-1)

	Mean Acquirer growth	Target growth		Mean Target growth	Acquirer growth
Acquirer growth quartile			Target growth quartile		
Q1	-.227	.069	Q1	-.547	.034
Q2	-.029	.039	Q2	-.121	.019
Q3	.072	.080	Q3	.036	.050
Q4	.366	.122	Q4	.481	.069
			Entrants	2.000	.096

Table 3. Which firms select into becoming an acquirer or target?

	Dependent variable is a dummy for ...			
	Acquiring firm in period *t*-1 to *t*		Target firm in period *t*-1 to *t*	
	(1)	(2)	(3)	(4)
Firm-level variables				
Size (log employment in *t*-1)	1.498 ***	1.386 ***	1.599 ***	1.543 ***
	(.101)	(.107)	(.069)	(.071)
Size² (log employment in *t*-1)	-.083 ***	-.067 ***	-.180 ***	-.177 ***
	(.011)	(.012)	(.011)	(.012)
Pre-merger growth rate (*t*-3 to *t*-1)	-.406 ***	-.369 ***	-1.107 ***	-1.095 ***
	(.094)	(.096)	(.065)	(.065)
Part of enterprise group	1.034 ***	1.051 ***	1.282 ***	1.228 ***
(*t*-2 or *t*-1, dummy)	(.045)	(.046)	(.046)	(.046)
FDI (*t*-2, dummy)	-.162 **	-.193 **	.198 **	.080 *
	(.077)	(.082)	(.093)	(.098)
Industry variables				
Declining industry	-.060		-.109 *	
(*t*-3 to *t*-1, dummy)	(.059)		(.060)	
Knowledge intensive sector	.164 *		.480 ***	
(dummy)	(.090)		(.088)	
Industry concentration ratio	-.710 ***		.286 **	
(*t*-1)	(.135)		(.130)	
Increasing industry concentration	-.479		1.376 *	
(*t*-3 to *t*-1, dummy)	(.866)		(.810)	
Sector FE (9 classes)	yes		yes	
Nace 3-digit FE (166 classes)		yes		yes
Year FE	yes	yes	yes	yes
Pseudo R-squared	.122	.147	.121	.143
No. of observations	166,367	147,089	719,577	638,972

Notes: Coefficient estimates from logistic regressions. Results are based on the sample of takeovers and non-merging firms in 2005-2012, which in columns (1) and (2) satisfy the preconditions of an acquirer in *t*-1 (at least 4 years old and 10 employees) and in columns (3) and (4) the preconditions of a target (at least 1 year old and 2 employees). Acquirers and targets are identified either using Commercial Court records or using the employee-flow method. Standard errors in parentheses; *, **, *** indicate significance at the 10%, 5%, or 1% level.

Table 4. Characteristics of acquirers, targets and control firms before and after matching

	Pre-matching[a]			Post-matching		
	Takeovers	Control group	Difference	Takeovers[b]	Control group[c]	Difference
	A	B	|A-B|	C	D	|C-D|
Number of firm-year observations						
Acquirers	2,517	164,877		2,209	1,734,611	
Targets	3,305	724,870		2,969	1,734,611	
1,2. Number of acquirers per year and (acquirer) industry						
Mean	3.4	140.2	-136.9	3.6	3.6	0.0
1,3. Number of targets per year and (target) industry						
Mean	3.4	613.5	-610.1	3.6	3.6	0.0
4. Acquirer part of enterprise group (*t*-1 or *t*-2)						
Share	47%	19%	28%	49%	49%	0%
5. Target part of enterprise group (*t*-1 or *t*-2)						
Share	38%	8%	29%	39%	39%	0%
6. Acquirer size (*t*-1)						
Mean	194	39	154	165	68	97
Median	[46]	[18]	[28]	[45]	[37]	[8]
7. Target size (*t*-1)						
Mean	41	12	29	33	14	19
Median	[13]	[4]	[9]	[13]	[9]	[4]
8. Acquirer pre-merger growth rate[d] (*t*-3 to *t*-1)						
Mean	.043	.081	.037	.048	.060	.011
Median	[.009]	[.047]	[.037]	[.014]	[.029]	[.015]
9. Target pre-merger growth rate (*t*-3 to *t*-1)						
Mean	-.005	.200	.205	-.011	.025	.036
Median	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]

Notes:

[a] Pre-matching statistics are based on the sample of takeovers and control (non-merging) firms in 2005-2012 that satisfy in *t*-1 the preconditions of acquirers or targets.

[b] Post-matching: takeovers without consistent employment information in each of the three years before the merger, and takeovers with an acquirer or target for which no valid matches could be found are excluded. For takeovers with multiple targets, target size and pre-merger growth are based on the sum of targets.

[c] Post-matching: control group consists of pairs of firms that match the target and acquirer characteristics. Reported results are based on weighted averages.

[d] Target pre-merger growth rates include entrants with growth rate equal to +2.

Table 5. Effect of takeovers on post-merger employment growth

(a) Year-on-year employment growth
Dependent variable: employment growth rate

	Takeover period (t-1 to t)		1st (t to t+1)		2nd (t+1 to t+2)		3rd (t+2 to t+3)	
			n th post-merger period					
Takeover effect	-.023	***	-.024	***	-.028	***	-.015	**
	(.003)		(.006)		(.007)		(.008)	
No. of observations	1,736,820		1,421,809		1,149,918		871,464	
No. of takeovers	2,209		1,927		1,562		1,132	

(b) Cumulative employment growth over *n*-year periods
Dependent variable: employment growth rate

	Takeover period (t-1 to t)		2-year period (t-1 to t+1)		3-year period (t-1 to t+2)		4-year period (t-1 to t+3)	
Takeover effect	-.023	***	-.046	***	-.070	***	-.083	***
	(.003)		(.007)		(.010)		(.014)	
No. of observations	1,736,820		1,421,809		1,150,387		873,052	
No. of takeovers	2,209		1,927		1,572		1,157	

(c) Growth acceleration
Dependent variable: difference in employment growth rate pre- and post-merger

	difference in 1-year growth rates (t-1 to t) - (t-2 to t-1)		difference in 2-year growth rates (t-1 to t+1) - (t-3 to t-1)	
Takeover effect	-.008	**	-.030	***
	(.004)		(.007)	
No. of observations	1,736,820		1,392,537	
No. of takeovers	2,209		1,863	

Notes: Regression coefficients show the average treatment effect on the treated using exact matching on acquirer and target characteristics. Takeovers in 2005-2012. Observations are dropped when employment is outside the sample period. Regressions include all firms active at the start of a period, both survivors and exiting firms. Standard errors in parentheses; *, **, *** indicate significance at the 10%, 5%, or 1% level.

Table 6. Differential effect of takeovers by single firm or industry characteristics

Dependent variable: cumulative employment growth rate

	Takeover period (t -1 to t)		2-year period (t -1 to t +1)		3-year period (t -1 to t +2)		4-year period (t -1 to t +3)	
Matching variables (all binary)								
Vertical merger	.005	(.006)	.013	(.014)	-.020	(.021)	-.007	(.029)
Acquirer high pre-merger growth[a]	.017 ***	(.006)	.019	(.013)	.009	(.021)	.011	(.029)
Target high pre-merger growth[a]	.015 **	(.006)	.021	(.013)	.023	(.021)	.035	(.029)
Acquirer part of enterprise group	.000	(.006)	.028 **	(.013)	.030	(.020)	.033	(.028)
Target part of enterprise group	.001	(.006)	.022 *	(.013)	.028	(.020)	.012	(.029)
Acquirer in largest size quartile	.006	(.007)	.027 *	(.015)	.021	(.022)	.040	(.031)
Target share < 25%	.007	(.006)	.030 **	(.014)	.023	(.021)	.051 *	(.029)
Other firm-level variables								
Acquirer invests in FDI	-.005	(.008)	.004	(.015)	-.007	(.027)	.042	(.033)
Target invests in FDI	-.005	(.012)	.023	(.024)	.040	(.038)	.071 *	(.040)
Industry variables								
Acquirer in Manufacturing	.000	(.007)	.000	(.017)	-.013	(.026)	-.060 *	(.036)
Target in Manufacturing	-.006	(.008)	-.006	(.018)	-.018	(.028)	-.055	(.041)
Acquirer in Trade or Services	.004	(.006)	.029 **	(.014)	.062 ***	(.021)	.098 ***	(.030)
Target in Trade or Services	.001	(.006)	.022	(.014)	.057 **	(.022)	.086 ***	(.031)
Acquirer in declining industry	.007	(.006)	.016	(.014)	.023	(.023)	-.021	(.040)
Target in declining industry	.008	(.006)	.010	(.014)	.008	(.023)	-.036	(.040)
Acquirer in concentrated industry	.005	(.011)	.023	(.024)	.032	(.041)	-.025	(.051)
Target industry is concentrating	-.007	(.020)	.005	(.035)	-.073	(.096)	-.035	(.124)
Target in high-tech industry	-.010	(.011)	.002	(.025)	.013	(.036)	-.015	(.052)
Years with takeover effect significantly different from average[b]								
t = 2007							.729 *	(.042)
t = 2011	.025 **	(.011)						

Notes: Regression coefficients show the average treatment effect on the treated using exact matching on acquirer and target characteristics for takeovers in 2005-2012. Each coefficient is estimated using a separate regression like equation (4), where the subset dummy is defined by a single characteristic. The table reports the δ coefficient of the interaction term between the takeover and subset dummies. The binary firm-level variables are always defined to yield a positive employment effect. Standard errors in parenthesis, *, **, *** indicate significance at the 10%, 5%, or 1% level.

[a] High growth means above the sample average

[b] We estimated regressions for takeovers in all 7 years in the sample and all 4 time periods and only report the coefficients that are statistically different from zero.

Table 7. Employment expansions for one type of takeovers: Acquirers in declining industries and high-growth targets

Dependent variable: cumulative employment growth rate

	Takeover period (t-1 to t)	2-year period (t-1 to t+1)	3-year period (t-1 to t+2)	4-year period (t-1 to t+3)
(a) Sample: all firms				
Subset 1: Acquirer in **declining** industry[a] & **Target** with **high** pre-merger growth				
Main takeover effect (β)	-.026 ***	-.051 ***	-.076 ***	-.089 ***
	(.003)	(.007)	(.010)	(.015)
Takeover effect in subset (β+δ)	.006	.011	.013	.079 *
	(.010)	(.018)	(.029)	(.042)
Difference in effects (δ)	.032 ***	.062 ***	.089 ***	.168 ***
	(.011)	(.020)	(.031)	(.045)
Subset 2: Acquirer in **declining** industry[a] & **Target** with **low** pre-merger growth				
Difference in effects (δ)	-.010	.009	-.016	-.054
	(.009)	(.017)	(.040)	(.080)
Subset 3: Acquirer in **growing** industry[a] & **Target** with **high** pre-merger growth				
Difference in effects (δ)	-.001	.007	.022	.030
	(.007)	(.014)	(.023)	(.032)
Number of observations	1,736,820	1,421,809	1,150,387	873,052
Takeovers in subset 1	171	164	104	41
Takeovers in subset 2	198	186	104	40
Takeovers in subset 3	373	300	273	231
(b) Sample: only takeovers with large target shares				
Subset 1 difference in effects (δ)	.047 **	.074 **	.099 **	.229 ***
	(.019)	(.030)	(.044)	(.082)
Subset 2 difference in effects (δ)	-.016	.012	-.003	-.052
	(.016)	(.032)	(.057)	(.135)
(c) Sample: only horizontal mergers				
Subset 1 difference in effects (δ)	.036 **	.050 **	.061 *	.167 **
	(.015)	(.024)	(.037)	(.074)
Subset 2 difference in effects (δ)	-.009	-.003	-.004	-.035
	(.011)	(.021)	(.043)	(.087)

Notes: Regression coefficients show the average treatment effect on the treated using exact matching on acquirer and target characteristics. Takeovers in 2005-2012. Results are based on equation (4), where the subset dummy is defined by the combined characteristics. The main takeover effect β represents the employment effect among all other pairs of firms not included in the subsets. The interaction effect δ represents the differential effect for the subset. Finally, β+δ represents the main effect within the subset. Its standard error is obtained by an estimation of the same equation where we reversed the subset dummies. Standard errors in parentheses; *, **, *** indicate significance at the 10%, 5%, or 1% level.

[a] We condition all subsets on acquirers being part of enterprise group

Table 8. Stronger employment reductions for one type of takeovers: Small acquirers and targets in manufacturing or construction

Dependent variable: cumulative employment growth rate

	Takeover period (t-1 to t)	2-year period (t-1 to t+1)	3-year period (t-1 to t+2)	4-year period (t-1 to t+3)
(a) Sample: all firms				
Subset 1: Acquirer of **below-average** size[a] & **Target** in **manufacturing or construction**				
Main takeover effect (β)	-.022 ***	-.039 ***	-.064 ***	-.074 ***
	(.003)	(.007)	(.010)	(.017)
Takeover effect in subset (β+δ)	-.046 ***	-.124 ***	-.139 ***	-.180 ***
	(.013)	(.035)	(.043)	(.061)
Difference in effects (δ)	-.024 *	-.084 **	-.075 *	-.106 *
	(.013)	(.036)	(.044)	(.062)
Subset 2: Acquirer of **above-average** size[a] & **Target** in **manufacturing or construction**				
Difference in effects (δ)	-.001	.033 **	.021	.058
	(.008)	(.015)	(.030)	(.040)
Subset 3: Acquirer of **below-average** size[a] & **Target** in **trade or services**				
Difference in effects (δ)	-.019 *	-.014	.010	.016
	(.010)	(.022)	(.034)	(.048)
Number of observations	1,736,820	1,421,809	1,150,387	873,052
Takeovers in subset 1	167	151	120	97
Takeovers in subset 2	254	214	180	137
Takeovers in subset 3	278	246	206	151

Notes: Note: Regression coefficients show the average treatment effect on the treated using exact matching on acquirer and target characteristics. Takeovers in 2005-2012. Results are based on equation (4), where the subset dummy is defined by the combined characteristics. The main takeover effect β represents the employment effect among all other pairs of firms not included in the subsets. The interaction effect δ represents the differential effect for the subset. Finally, β+δ represents the main effect within the subset. Its standard error is obtained by an estimation of the same equation where we reversed the subset dummies. Standard errors in parentheses; *, **, *** indicate significance at the 10%, 5%, or 1% level.

[a] We condition all subsets on acquirers experiencing below-average growth before the merger.

Table A.1 Description of the variables

Explanatory variables	Description
Firm-level variables	
Size in t-1	The number of employees a firm employs at the last point of observation before the takeover, i.e. at June 30 of year t-1.
Pre-merger growth rate (t-3 to t-1)	The employment growth rate in the 2-year period before the takeover: $g_i = (E_{it-1} - E_{it-3})/\overline{E}_i \qquad with\ \overline{E}_i = (E_{it-1} + E_{it-3})/2$
Firm is part of an enterprise group (dummy)	Takes a value of one if firm i owns at least 50 percent of the shares of another Belgian firm or is owned by another Belgian firm for at least 50 percent in t-1 or t-2.
FDI (dummy)	Takes a value of one if firm i is either receiver or sender of FDI in t-2.
Industry variables	
Declining industry (dummy)	Takes a value of one if the industry at the Nace 2-digit level exhibited negative output growth between t-3 and t-1.
Knowledge intensive industry (dummy)	Takes a value of one if the industry at the Nace 2-digit level is high-tech manufacturing industry or a knowledge-intensive service industry (source: Eurostat,
Industry concentration ratio	Employment share of the four largest firms at the Nace 3-digit industry level (166 industries) in t-1.
Increasing industry concentration (dummy)	Takes a value of one if the industry concentration ratio increases from t-3 to t.
Industry classifications	
Nace 3-digit level	166 industries
Nace 2-digit level	76 industries
Sector groups	9 groups: Agriculture; Manufacturing; Energy; Construction; Trade; Transportation; Accommodation; Business services; Other services.

Table A.2 Share of firms involved in a restructuring event

	Number of obs.	Share in event		
	(t)	(t to t+1)	(t to t+2)	(t to t+3)
Takeovers	2,259	.14	.25	.34
Firms in control sample	128 025	.02	.03	.05

Table A.3 Which firms select into acquirer or target: identified using different methods?

	Dependent variable is a dummy for ...			
	Acquiring firm in period *t* -1 to *t*		Target firm in period *t* -1 to *t*	
Takeovers are identified by…	Commercial Court	Employee-flows only	Commercial Court	Employee-flows only
	(1)	(2)	(3)	(4)
Size (log employment in *t* -1)	1.527 ***	1.252 ***	1.157 ***	2.385 ***
	(.141)	(.156)	(.085)	(.139)
Size² (log employment in *t* -1)	-.086 ***	-.054 ***	-.118 ***	-.319 ***
	(.015)	(.017)	(.013)	(.024)
Pre-merger growth rate (*t* -3 to *t* -1)	-.333 ***	-.399 ***	-1.310 ***	-.804 ***
	(.126)	(.145)	(.087)	(.096)
Part of enterprise group	1.345 ***	.623 ***	1.463 ***	.888 ***
(*t* -2 or *t* -1, dummy)	(.061)	(.070)	(.061)	(.073)
FDI (*t* -2, dummy)	-.238 **	-.168	.195 *	-.209
	(.102)	(.131)	(.117)	(.182)
Nace 3-digit FE (166 classes)	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Pseudo R-squared	.167	.111	.143	.121
No. of observations	125,682	125,849	548,722	546,297

Notes: Coefficient estimates from logistic regressions. Results are based on the sample of takeovers and non-merging firms in 2005-2012, which in columns (1) and (2) satisfy the preconditions of an acquirer in t-1 (at least 4 years old and 10 employees) and in columns (3) and (4) the preconditions of a target (at least 1 year old and 2 employees). Standard errors in parentheses; *, **, *** indicate significance at the 10%, 5%, or 1% level.

Table A.4 Robustness check for the effect of takeovers on employment growth: Alternative sampling schemes for the number of controls

Dependent variable: cumulative employment growth rate

	Takeover period (t-1 to t)	2-year period (t-1 to t+1)	3-year period (t-1 to t+2)	4-year period (t-1 to t+3)
(a) Full sample				
Takeover effect	-.023***	-.046***	-.070***	-.083***
	(.003)	(.007)	(.010)	(.014)
No. of observations	1,736,820	1,421,809	1,150,387	873,052
No. of takeovers	2,209	1,927	1,572	1,157
(b) Subsample with max 10 controls per takeover				
Takeover effect	-.023***	-.047***	-.069***	-.084***
	(.003)	(.007)	(.010)	(.015)
No. of observations	23,271	20,242	16,524	12,199
No. of takeovers	2,209	1,927	1,572	1,157
(c) Subsample with exact 10 controls per takeover				
Takeover effect	-.024***	-.046***	-.069***	-.075***
	(.003)	(.007)	(.011)	(.015)
No. of observations	21,978	19,052	15,552	11,522
No. of takeovers	1,998	1,732	1,412	1,042
(d) Subsample with exact 30 controls per takeover				
Takeover effect	-.022***	-.044***	-.072***	-.080***
	(.003)	(.008)	(.012)	(.016)
No. of observations	55,521	48,050	39,246	28,861
No. of takeovers	1,791	1,550	1,266	931
(e) Subsample using only firms that survive to the end of the period (t+3)				
Takeover effect	-.027***	-.055***	-.074***	-.083***
	(.004)	(.009)	(.012)	(.014)
No. of observations	873,052	873,052	873,052	873,052
No. of takeovers	1,157	1,157	1,157	1,157

Notes: The results in panel (a) replicate the results of Table 5 panel (b) and serve as benchmark.

Table A.5 Robustness check for the effect of takeovers on employment growth: Alternative treatment effect estimators (within cells)

Dependent variable: cumulative employment growth rate

	Takeover period (t-1 to t)	2-year period (t-1 to t+1)	3-year period (t-1 to t+2)	4-year period (t-1 to t+3)
(a) Exact matching				
Takeover effect	-.022***	-.044***	-.072***	-.080***
	(.003)	(.008)	(.012)	(.016)
No. of observations	55,521	48,050	39,246	28,861
No. of takeovers	1,791	1,550	1,266	931
(b) Propensity score matching				
Takeover effect	-.021***	-.039***	-.070***	-.063***
	(.004)	(.008)	(.012)	(.017)
No. of observations	54,963	47,492	38,688	28,520
No. of takeovers	1,773	1,532	1,248	920
(c) Inverse probability-weighted regression adjustment				
Takeover effect	-.021***	-.041***	-.064***	-.070***
	(.003)	(.007)	(.011)	(.015)
No. of observations	54,963	47,492	38,688	28,520
No. of takeovers	1,773	1,532	1,248	920

Notes: All estimates are based on a subsample with exactly 30 control observations per takeover. The results in panel (a) replicate the results from Table A.4 panel (d), and serve as a benchmark. The matching estimators in panel (b) and (c) will not necessarily use the same controls for each takeover as the ones we selected for exact matching. For the estimations in panel (b), we impose that each firm involved in a takeover should be matched with at least five similar firms, the so-called 'nearest neighbors'; in addition, we impose that the maximum distance for which two observations are potential neighbors is 0.05 standard deviation of the propensity scores. These restrictions slightly reduce the number of observations. We use exactly the same observations for the estimations in panel (c).