For Online Publication: Appendix for "Mergers and Managers: Manager-Specific Wage Premiums and Rent Extraction in M&As"

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1 Theoretical Framework

We introduce a simple two-period wage bargaining model between a firm's manager and a homogeneous group of workers. We use the model to show how individual managers' styles—by which we mean their propensity to pay above-market wages—affect wage setting and profits. We then show how mergers create value by replacing inefficient managers, and disentangle the effects of various channels—efficiency, monopoly power, and rent extraction—on employment and wages. Finally, we develop an empirical measure of manager styles based on the relationship between manager turnovers and changes in wages and productivity.

The economy has a large number of firms and a large number of workers. Each firm has one manager. For simplicity, we assume that firms operate a production technology that uses labor as the only input. The production function is $Y_j = T_{jm}F(L_j)$, where L_j is the number of workers employed at firm j. T_{jm} denotes firm j's total factor productivity (TFP) when it is managed by manager m. We assume that $F(.)$ is strictly increasing, strictly concave, and continuously differentiable in L. The timing is as follows: in period 1 managers bargain over wages with the workers. The managers then make production decisions and hire workers in period 2. We solve for a subgame perfect equilibrium of this model.

At period 2, demand for firm j is given by $q_j(p_j)$, and the corresponding inverse demand is $p_j(L_j) = q_j^{-1}(T_{jm}F(L_j))$. Firms solve the following profit maximization problem (note that wage rate is assumed to be exogenous in this period):

$$\max_{L_j} \pi_j = p_j(L_j)T_{jm}F(L_j) - w_jL_j \tag{1}$$

The first-order condition is:

$$w_j = \left(1 - \frac{1}{\varepsilon_j}\right) p_j T_{jm} F'(L_j) \tag{2}$$

where $\varepsilon_j = -\frac{\partial q_j}{\partial p_j}\frac{p_j}{q_j}$ is the price elasticity of demand and $\varepsilon_j > 1$.

At period 1, managers bargain with their respective unions over wages. We assume that the solution is characterized by a generalized Nash bargaining outcome given by the following program:

$$\max_{w_j}(w_j - b_j)^{\beta}(\pi_j + \phi_m w_j \overline{L_j})^{1-\beta}$$

where β is workers' bargaining power at firm j and b_j is the outside option of workers at firm j. The union maximizes the wages paid to workers.[1] We assume that managers maximize the sum of firm profits and their private benefits from higher wages. The reason is that managers have agency costs and prefer to enjoy a "quiet life" (Bertrand and Mullainathan 2003), or they use high wages as a substitute for monitoring efforts (Krueger 1991; Acemoglu and Newman 2002). They may also simply enjoy paying some workers high wages (Landier, Nair and Wulf 2009; Yonker 2017). The term $\phi_m w_j \overline{L_j}$ captures the private benefits to managers, where ϕ_m is a manager-specific parameter, and $\overline{L_j}$ is the past average employment at firm j.[2] Private benefit is proportional to the firm's average employment but does not depend on employment during the current period, and therefore it captures managers' preferences for higher wages but *not* higher employment. Since the term does not contain current-period employment, it does

[1]There is no employment in the union's utility function because (1) the majority of firm-level bargaining agreements cover only wage increases and no employment-related outcomes; (2) since most of our sample is before the Great Recession, we assume that employment is mainly adjusted along the hiring margin, and involuntary separations do not depend on bargained wage levels, which we verify in the data later. The absence of employment in bargaining agreements is also inconsistent with the class of efficient bargaining models, in which managers and workers bargain to Pareto-efficient employment and wage levels.

[2]The term is scaled by average employment level such that the private benefit is proportional to firm size (for example, the cost of bargaining may be higher in bigger firms). Nevertheless, our qualitative predictions remain the same when private benefit is $\phi_m w_j$.

not enter the maximization problem in period 2. The resulting outcome is:

$$w_j = (1-\beta)b_j + \beta\frac{p_j T_{jm} F(L_j)}{L_j - \phi_m \overline{L_j}} \tag{3}$$

Equations (2) and (3) jointly determine wage w_j and employment L_j. The following proposition summarizes how manager styles in wage setting ϕ_m affect firm outcomes:

Proposition 1. *Wage w_j is increasing in $\phi_{m(j)}$, and employment L_j and profit π_j are decreasing in $\phi_{m(j)}$, where $m(j)$ indexes the manager working at firm j.*

Managers also differ in their productivity T_{jm}, and the following proposition summarizes how managers' productivity affects firm outcomes:

Proposition 2. *Wage w_j, employment L_j and profit π_j are increasing in manager's productive efficiency T_{jm}.*

To ensure that profits are nonnegative, the maximum ϕ_m must satisfy:

$$\phi_{m(j)} \leq 1 - \frac{\beta}{1-(1-\beta)\frac{b_j L_j}{p_j T_{jm} F(L_j)}} \tag{4}$$

The right-hand side of this equation depends on the ratio of average productivity $\frac{p_j A_j F(L_j)}{L_j}$ to outside option b_j. When the outside option is low relative to productivity, the right-hand side is close to $1-\beta$; when the outside option is close to productivity, the right-hand side is almost zero.

Proposition 3. *Let $\overline{\phi}_j$ be the maximum ϕ_m such that firm j has nonnegative profits. $\overline{\phi}_j$ is increasing in productivity T_j and decreasing in demand elasticity ε_j. In other words, $\overline{\phi}_j$ is higher in industries with higher concentration.*

Managers with higher ϕ_m ("soft" managers) lead to higher wages and lower profits, which provides opportunities for acquiring firms to extract rents. Managers with low TFP lead to lower profits and provide opportunities for productivity-enhancing mergers. The following corollary describes how different channels of mergers affect employment, wages, and productivity in the target firms.

Corollary. *Mergers raise profits and create value through the following channels:*
(1) Rent-extracting mergers: mergers replace soft managers, i.e., $\phi_{m(j)}$ decreases, which reduces wages, increases employment, and does not affect TFP at target firms;
(2) Productivity-enhancing mergers: mergers replace inefficient managers, i.e., T_{jm} increases, which increases wages and TFP at target firms, and has ambiguous effects on employment;
(3) Market-power-increasing mergers: mergers increase market power and markups in the product market, i.e., ε_j decreases, which increases wages and TFP and reduces employment.

Among all the channels, only the rent extraction channel reduces wages at the target firms. The reason is that, holding the bargaining power and manager preferences fixed, mergers that increase productivity through efficiency improvements or market power will lead to higher wages.

The model predictions allow us to estimate manager styles and manager productivity from the data. We can approximate the wage rule as:

$$\log w_j = (1-\beta)\log b_j + \beta \log\left(\frac{p_j T_{jm} F(L_j)}{L_j}\right) + \beta\phi_{m(j)} \tag{5}$$

In this equation log wage is the sum of three parts: the first part is reservation wage, the second part is sharing of average log value added per worker, and the third part is due to manager discretion. Therefore, in the panel data, when we include both firm fixed effects and manager fixed effects and control for productivity, the manager fixed effects would identify the term $\beta\phi_m$. Since the two-way fixed effects model requires a lot of manager mobility across firms, we also take a complementary approach of regressing wages on productivity, and industry and region fixed effects interacted with year fixed effects, and the residual from this regression is $\beta\phi_m$ if the error terms are uncorrelated with manager styles.[3]

Similarly, we can estimate manager productivity using the two-way fixed effects framework with the dependent variable being the TFP. Assume that the TFP can be decomposed into a firm-specific component and a manager-specific component ($\log T_{jm} = \log A_j + \log\theta_m$),

[3]The interactions of industry and region fixed effects with year fixed effects control for the outside option b_j. We assume that the outside option is not affected by managers. Otherwise changing the outside option b_j has the same effects on wages and employment as changing ϕ_m, but only changes the interpretation: "soft" managers give workers better outside options in wage negotiations instead of enjoying private benefits from high wages.

then manager fixed effects from the two-way fixed effects regression identifies individual managers' productivity θ_m. The log value added per worker is: $\log(p_j T_{jm} F(L_j)/L_j) = \log A_j + \log \theta_m + \log(p_j F(L_j)/L_j)$. Conditional on one firm, a more efficient manager also increases value added per worker, but a 1% increase in θ_m increases value added per worker by less than 1% due to decreasing returns to scale.

In our stylized model, soft managers get higher private benefits from paying higher wages; alternatively, soft managers may give workers higher bargaining power β. In a more general model with both heterogeneous private benefits and bargaining power among managers, the treatment effect of managers we identify combines various structural parameters. However, our approach still identifies the correct ranking of managers' effect on wage premiums as long as managers' bargaining power is uncorrelated with their productivity. Our qualitative results also remain unchanged: soft managers raise wages and lower profits, and therefore are replaced in M&As.

2 Additional Results

2.1 Alternative Matching Strategies

2.1.1 Non-parametric matching

We consider nonparametric comparisons that control for the cross-product of our categorical variables as in Davis et al. (2014). We construct cells using a fully saturated interaction of 127 three-digit industries, 8 establishment size groups and 4 establishment age groups. We estimate the following regressions for all stayers:

$$w_{ijt} = \alpha_{ij} + \gamma_t + \sum_{\tau=-3}^{5} \delta_\tau D_{it}(\tau) + \beta X_{it} + \epsilon_{it}$$

where $D_{it}(\tau)$ is a dummy indicating the year relative to merger. For non-target firms we assign $\tau = -1$. The control variables X_{it} contains interaction of year dummies and dummies for each cell. The coefficients of interest are δ_τ, which captures the effect of merger in year τ in the target establishments and are normalized to zero in $\tau = -1$. We also run the same specification for the matched control establishments in our baseline propensity score matching procedure.

Angrist and Pischke (2008) argue that OLS and matching yield different results because of different weighting, but in general differences between matching and OLS are not of much empirical importance. Column 5 of Table A3 shows that the OLS results are similar to our baseline matching method. Column 6 shows that the matched control firms do not exhibit different trends from other firms conditional on the covariates, suggesting that the spillover effects of mergers on the matched control firms are negligible.

2.1.2 Synthetic control

We test the robustness of our matching framework through an alternative strategy based on a synthetic control estimator (Abadie and Gardeazabal, 2003, Abadie et al., 2010).

We build a synthetic control for each establishment target using only average information in the years [-4,-2] relative to the acquisition date. We create the synthetic control from a pool of pre-selected establishments, which we select as being in the same industry and having similar employment and wage levels three years before the audit to reduce computation. The synthetic control is obtained by weighting all establishments in the control pool so as to minimize the pre-treatment differences with the treated establishment. In particular, this methodology allows to flexibly control for unobserved factors that affect common trends in both the treatment and control groups (Abadie et al., 2010). While this empirical strategy is commonly used in cases of only one treated unit, we follow a strategy similar to Acemoglu et al. (2016) to extend the methodology to the case of multiple treated units. Hence, we first construct the synthetic control for each establishment, and we then aggregate the individual treatment effects through a re-weighting using the quality of each match. Our estimate is computed as follows:

$$\hat{\theta}(\tau) = \frac{\sum_{i \in \text{Treatment group}} \frac{y_{i\tau} - \hat{y_{i\tau}}}{\hat{\sigma_i}}}{\sum_{i \in \text{Treatment group}} \frac{1}{\hat{\sigma_i}}}$$

where $\hat{y_{i\tau}}$ is the outcome of the synthetic control unit. $1/\hat{\sigma_i}$ measures the goodness of fit for each match, so that better matches are given more weight in the estimation. To construct the confidence intervals, we randomly draw 5,000 placebo treatment groups from the control group

– with each group having the same size as the real treatment group. We compute the wage effect of M&As for these placebo treatment groups, and construct the confidence intervals for hypothesis testing of whether the coefficient is significantly different from zero. The effect is significant at 5% if it does not belong to the interval that contains the [2.5, 97.5] percentiles of the effect for placebo treatment groups. Result is shown in Figure A16.

2.2 Job Inflow and Outflow

To examine how job inflow and outflow change around time of M&As, we define job inflow between year 0 and year 1 as the number of workers joining the firm during the period divided by the employment in year 0, and job outflow as the number of workers leaving the firm during the period divided by employment in year 0. We then estimate the equation:

$$y_{jt} = \gamma_t + \sum_{\tau=-3}^{5} \lambda_\tau D_{jt}(\tau) + \beta X_{jt} + \epsilon_{jt}$$

where λ_τ captures the difference between treated and control establishment in terms of job inflow and outflow rates. We control for industry-year fixed effects to absorb industry-specific trends. Figure A9 shows that both job inflow and job outflow increase following mergers.

How does cutting wages affect job flows? To answer this question, we look at the effects of mergers on job inflow and outflow separately for high-wage and low-wage establishments. In Section 4.3 we have established that all of the wage cuts are concentrated in high-wage establishments. Figure A20 shows that both high-wage and low-wage establishments experience a rise in job outflow rates after mergers, while only high-wage establishments experience a large rise in job inflow rates after mergers. The average quality of joining workers in high-wage establishments increases, while the average average of joining workers in low-wage establishments does not change after mergers. This indicates that mergers lead to wage cuts in high-wage establishments, but also lead to more hiring of high-skilled workers in high-wage establishments. By reducing the wage premium in establishments with soft managers, mergers allow the target firms to hire more high-wage workers.

2.3 Wage Changes of All Initially Employed Workers

We investigate the selection issue by looking at the effects of mergers on the wages and departure rates for cohorts of workers initially employed in target firms at the time of acquisition. We estimate the following regression, which includes all workers who are in the target or control establishments in $\tau = -1$ regardless of whether they move to another establishment in $\tau > 0$:

$$y_{it} = \alpha_i + \gamma_t + \sum_{\tau=-3}^{5} \lambda_\tau D_{it}(\tau) + \sum_{\tau=-3}^{5} \delta_\tau D_{it}(\tau) \times Target_i + \beta X_{it} + \epsilon_{it} \quad (6)$$

This is the same as the cohort-based approach in Hummels, Munch and Xiang (2018).

Figure A13 shows that mergers reduce wages for workers initially employed in target firms at time of merger. The wage declines are slightly larger than those of workers staying in target firms due to the additional negative effects of job displacement (Jacobson, LaLonde and Sullivan 1993). However, although the effect on unemployment peaks at one year after merger, the negative wage effects are persistent and seemingly irreversible, which is consistent with the loss of firm-specific wage premiums.

3 Data Appendix

3.1 Identify Managers

We define managers using occupation codes (ISCO-88) and job hierarchy (PSTILL). A worker is defined as a manager if the occupation code belongs to the manager occupation group or if the worker is in the highest job hierarchy. About 6% of all the workers are managers, and we are able to identify at least one manager for about 60% of all establishment-year observations, and for 80% of the establishment-year observations with at least 10 employees.

For each firm we select one manager with the highest rank. The highest ranked occupation code is 1210 (directors and chief executives). If no worker has occupation code equal to 1210, then the highest ranked manager is someone with a managerial occupation code (between 1221 and 1319) and has highest job hierarchy (PSTILL=31). If no one satisfies the criteria, then the highest ranked manager is someone with a managerial occupation code or highest job hierarchy. If multiple individuals have the same highest ranked occupation code and the highest job hierarchy, then we select the manager with the highest total income as the top manager.

3.2 Comparing with External Datasets of M&As

Figure A3 compares the number of mergers in our administrative dataset with the number of mergers in Denmark in Zephyr and SDC datasets. In all datasets number of mergers is increasing before the financial crisis and declines afterwards. The administrative dataset has about 30-40% more mergers in years before the financial crisis.

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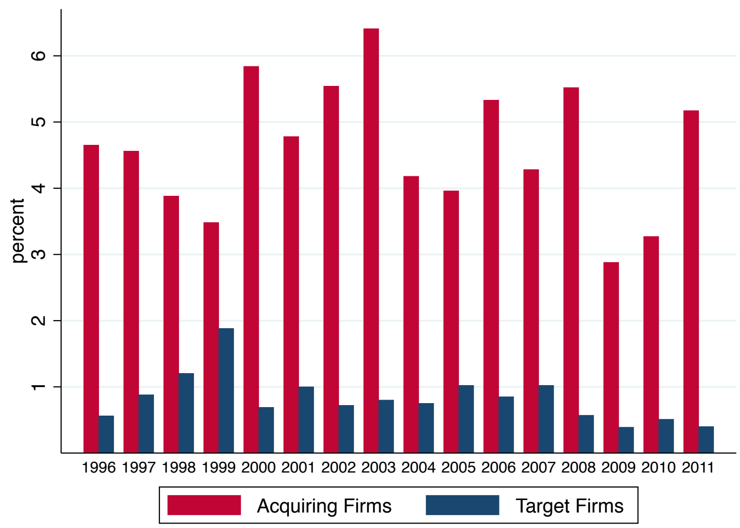
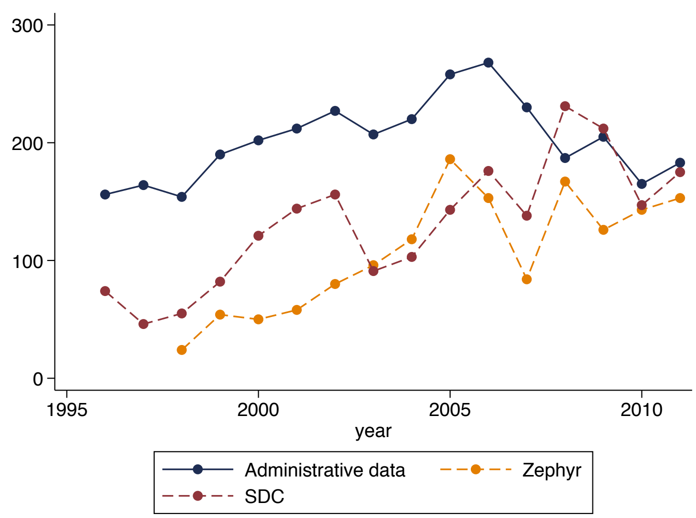
Figure A1: Percentage of employment in target or acquirer firms



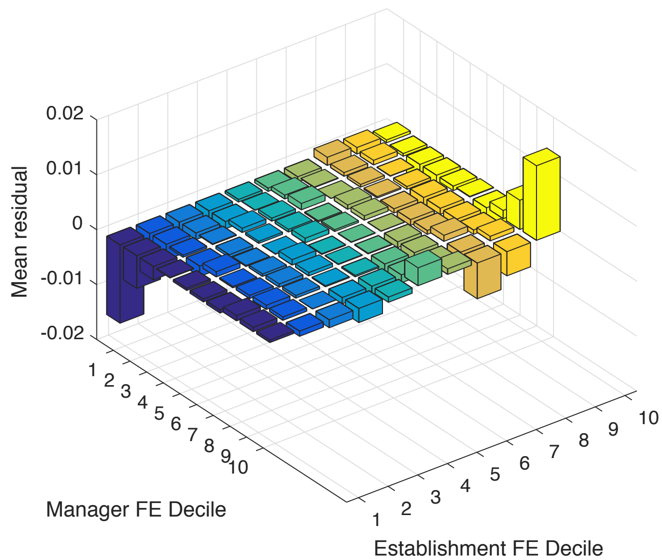
Notes: This figure shows the share of all employed workers in Denmark that works in acquired or acquiring firms in each year. We only include workers who are full-time employees and are between 25 and 60 years old.

Figure A2: Compare Mergers in Administrative Datasets and External Datasets



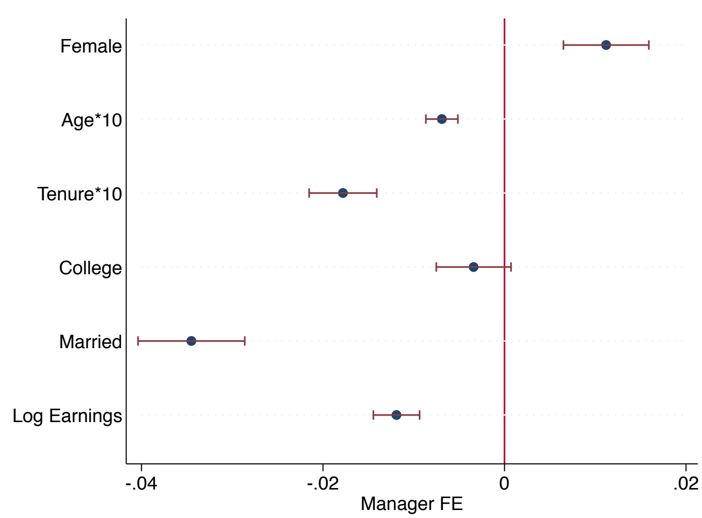
Notes: This figure shows the number of merger transactions in Denmark by year from 1996 to 2011. The solid line is the number of merger transactions in our data, the red dashed line is the number of transactions from the SDC Platinum data, and the orange dashed line is the number of transactions from BvD Zephyr data. Transactions in which one of the parties is a foreign company are not included. For transactions involving multiple firms each transaction is only counted once.

Figure A3: Mean residuals by deciles of manager/establishment fixed effects



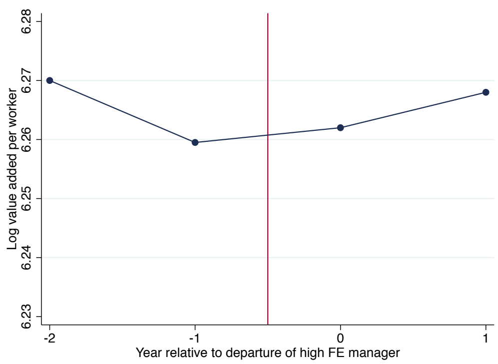
Notes: Figure shows mean residuals from estimating manager FE (equation 2) with cells defined by decile of estimated establishment effect, interacted with decile of estimated manager effect.

Figure A4: Characteristics of soft managers

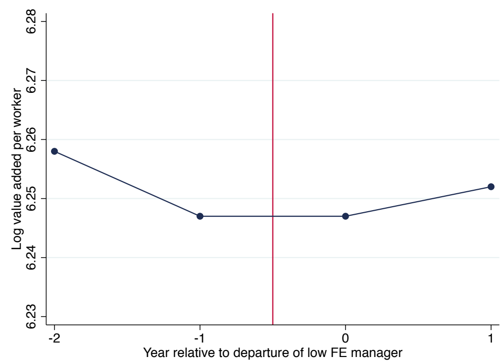


Notes: This figure shows the regression coefficients of manager fixed effects in wages on managers' characteristics. The dependent variable is manager fixed effects and the regression is weighted by the inverse standard errors of the estimated manager fixed effects. Each row is a separate regression. Ninety-five percent confidence intervals shown.

Figure A5: Event study of exogenous manager departures on productivity



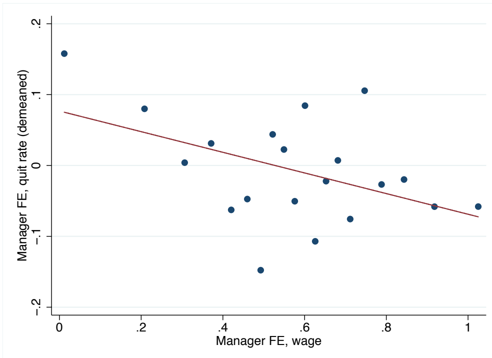
(a) High FE manager departure



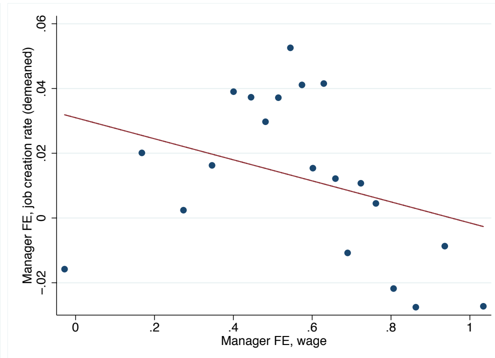
(b) Low FE manager departure

Notes: This figure shows the changed in log value-added per worker around exogenous departure of managers. Year 0 is the year when the manager leaves or dies, and we only include managers that had stayed in the same firm for at least three years before they leave and had never been employed since leaving. We reestimate the manager fixed effects for all managers using data outside the four-year window used for the event studies.

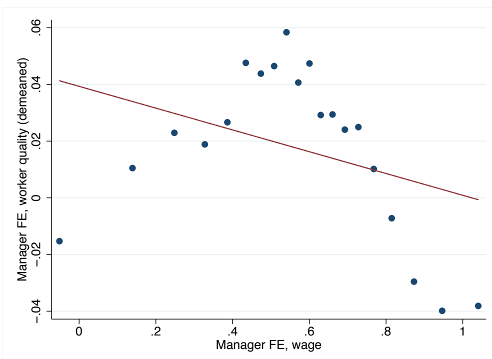
Figure A6: Correlation between manager fixed effects



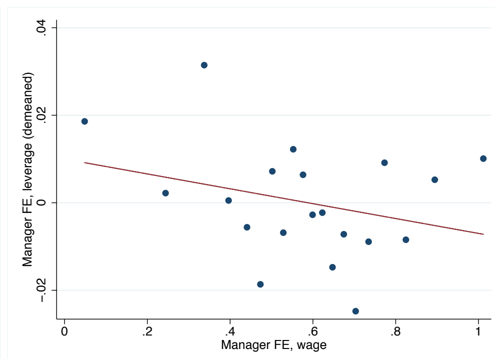
(a) Firing rate



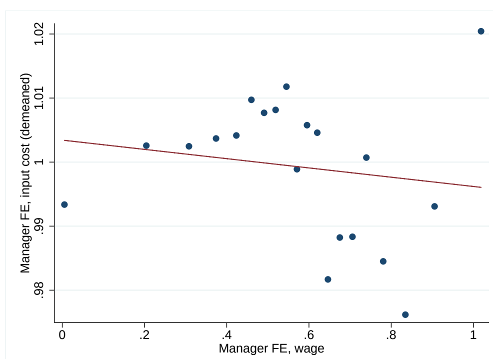
(b) Hiring rate



(c) Worker Quality



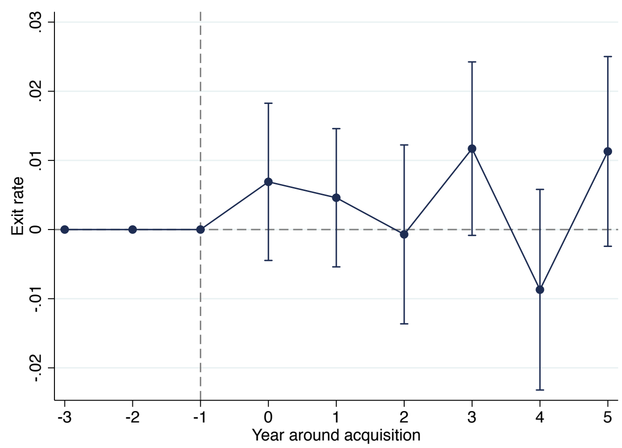
(d) Leverage



(e) Input cost

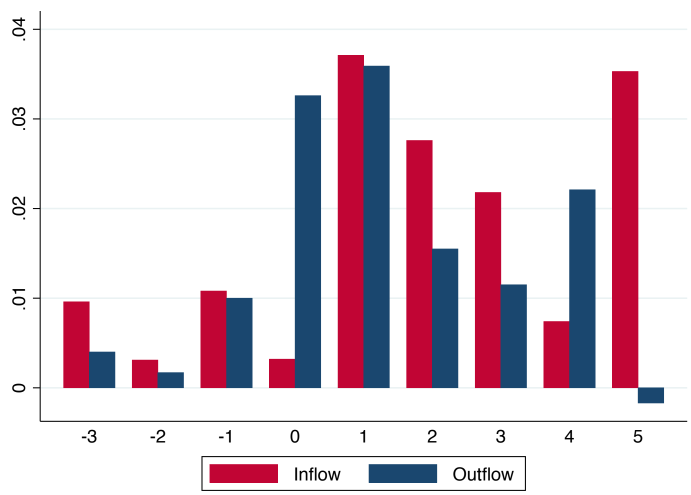
Notes: The graph shows the binscatter plots of manager fixed effects for various outcomes against manager fixed effects for wages. Each dot contains the same number of observations. In (a), on the y axis is manager FE in terms of the share of workers leaving the establishment in each year. In (b), on the y axis is manager FE in terms of share of new entrants every year. In (c), on the y axis is manager FE in terms of average worker quality, where worker quality is measured using person fixed effects in an AKM regression with person fixed effects and establishment fixed effects. In (d), on the y axis is manager FE in terms of leverage (total debt divided by book value of assets). In (e), on the y axis is manager FE in terms of log input costs.

Figure A7: Effects of merger on establishment exit



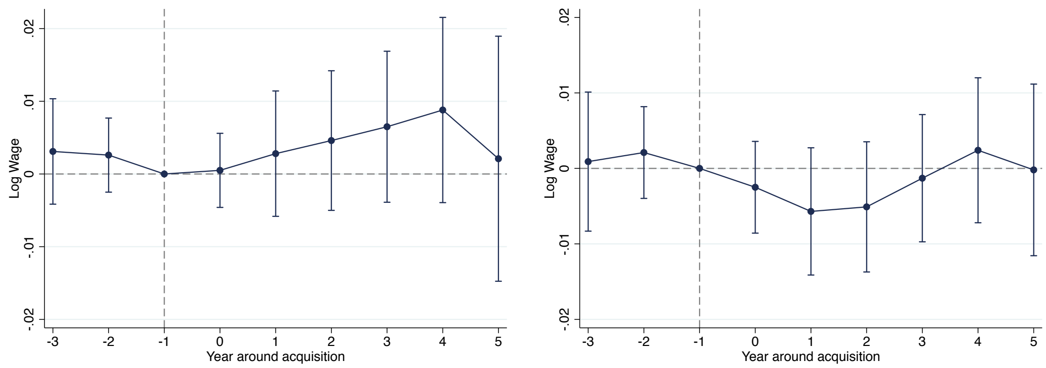
Notes: The figure shows regression coefficients and associated confidence intervals for the difference between treatment and comparison group in a given year τ relative to the year of acquisition in the treatment group establishments, i.e., the δ_τ from the difference-in-differences model in (4). The coefficient in $\tau = -1$ is normalized to zero. Regressions are weighted by average establishment employment between $\tau = -3$ and $\tau = -1$. The outcome variable is a dummy variable that equals one if the establishment exits in the following year. The vertical lines denote 95% confidence intervals based on standard errors clustered at the establishment level.

Figure A8: Changes in job inflow and outflow in target establishments around mergers



Notes: This figure shows differences in the inflow and outflow of workers between target establishments and control establishments. The regression controls for industry-year fixed effects. Inflow (outflow) at year τ is calculated as the number of entrants (leavers) between year $\tau - 1$ and year τ divided by employment in year $\tau - 1$.

Figure A9: Effects of merger on wages of workers in acquiring establishments

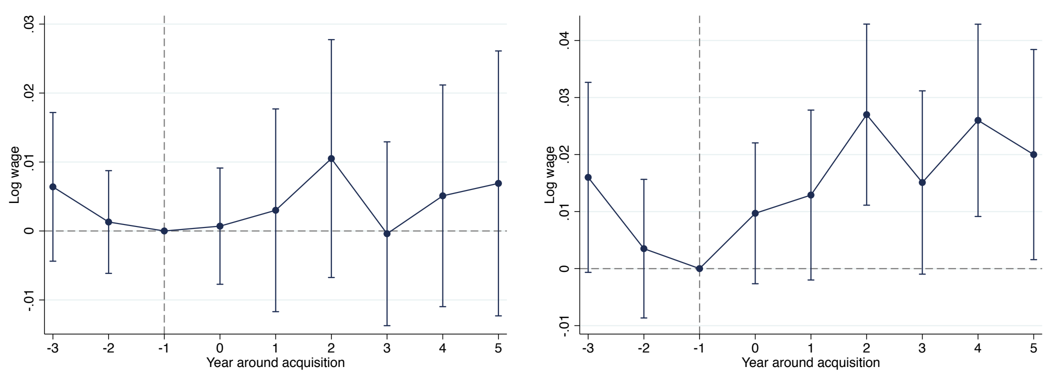


(a) Staying workers

(b) All initially employed workers

Notes: This figure shows the effect of mergers on workers' annual wages in acquiring firms. The left figure shows the effects on wages of all workers staying in acquiring establishments, and right figure shows the effects on wages of all workers employed in acquiring firms in the year before the merger. Establishments that have acquired multiple times are excluded. Ninety-five percent confidence intervals shown.

Figure A10: Wage effects of public sector mergers

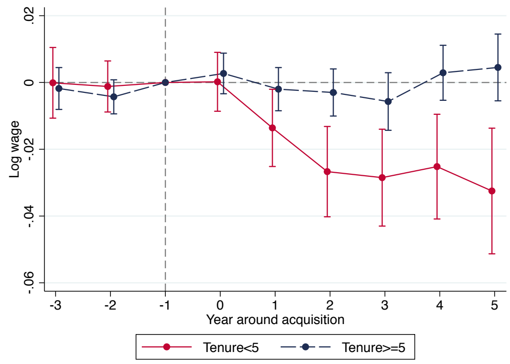


(a) Staying workers

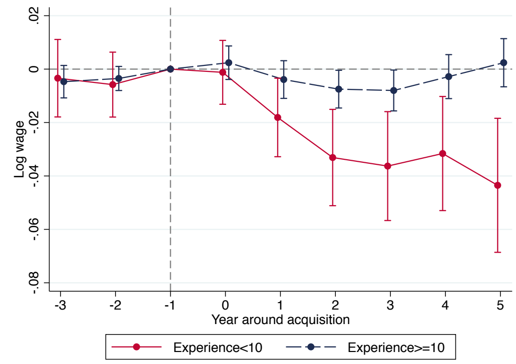
(b) All initially employed workers

Notes: The figure shows regression coefficients and 95% confidence intervals for the difference between wages at target and control establishments in the public sector. Public sector industries are defined as industries comprising of firms owned by the government, including education, public administration, governments, utility services, health services, etc. The left figure plots wage effects for staying workers, i.e. δ_τ in equation (10); the right figure plots wage effects for all initially employed workers, i.e. δ_τ in equation (16).

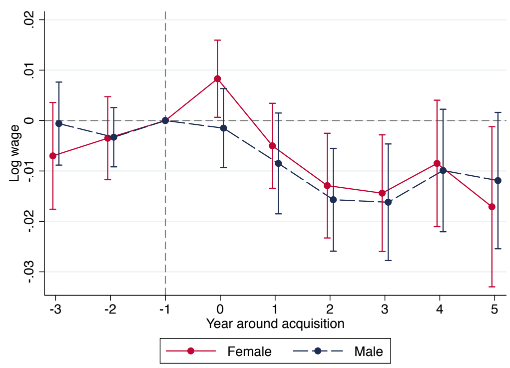
Figure A11: Heterogeneity by worker covariates



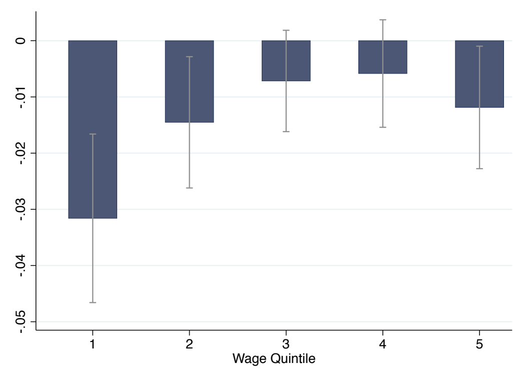
(a) By tenure



(b) By experience



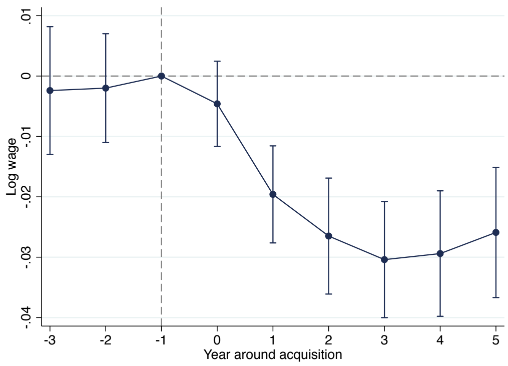
(c) By gender



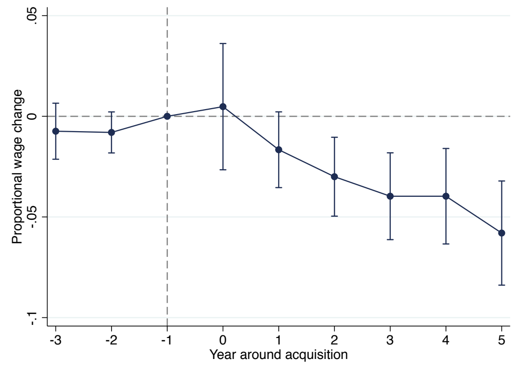
(d) By pre-merger wage quintile

Notes: The figure shows regression coefficients and associated confidence intervals for the difference between staying workers at target and control establishments for different groups of workers. We estimate variations of equation (5) adding interactions of worker covariates with the period dummies, as well as interactions of covariates with period dummies and treatment status, and plot the coefficients for the interactions of covariates with period dummies and treatment status. The worker characteristics (tenure, experience and wage quintile) are calculated at year -1 (one year before the merger takes place). In the regression sample, the median experience is 15 years and the median tenure is 4 years, and 37% are female. The coefficient in $\tau = -1$ is normalized to zero. The vertical lines denote 95% confidence intervals based on standard errors clustered at the establishment level.

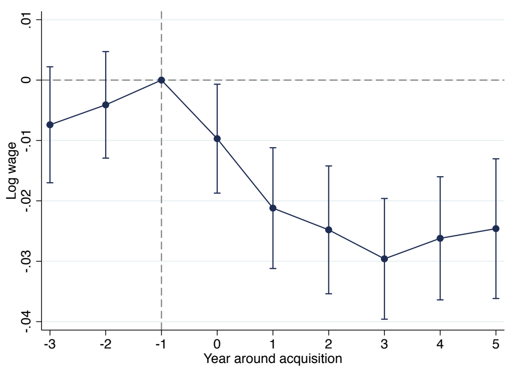
Figure A12: Changes in all initially employed workers' wages after M&As



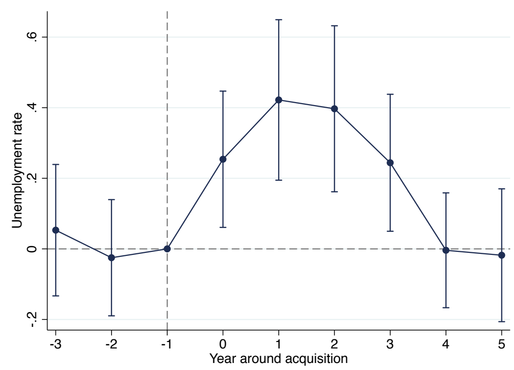
(a) Log annual wage



(b) Proportional wage change



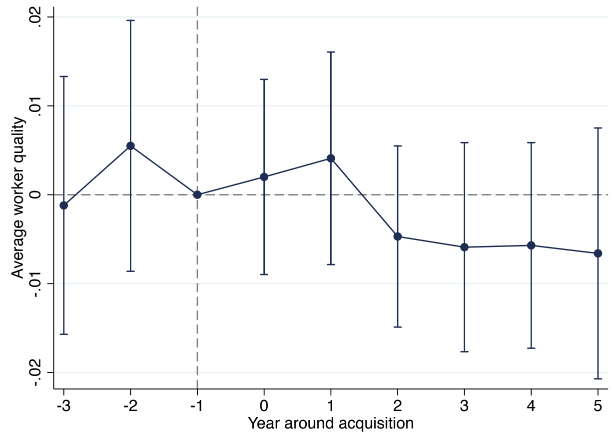
(c) Log hourly wage



(d) Unemployment

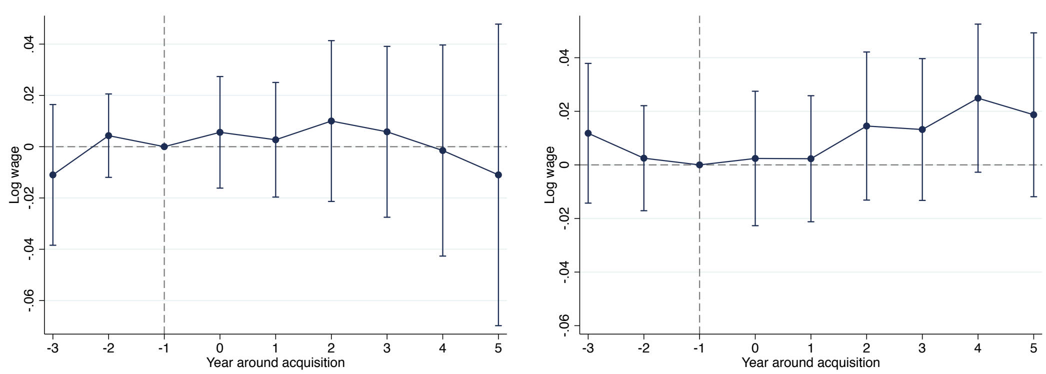
Notes: The figure shows regression coefficients and associated confidence intervals for the difference between workers initially employed at target and control establishments at time $\tau = -1$, i.e., the δ_τ from the difference-in-differences model (6) in the Appendix. The coefficient in $\tau = -1$ is normalized to zero. All regressions control for person fixed effects and year fixed effects. The outcome variable in panel (a) is log annual labor earnings. The outcome variable in panel (b) is proportional change in annual earnings relative to the initial annual earnings before merger ($w/w_0 - 1$). Observations with zero earnings are included in (b) and not in (a). The outcome variable in (c) is log hourly wage, which is calculated as annual labor income divided by annual hours worked. The outcome variable in (d) is a dummy variable for unemployment multiplied by 100, where unemployment is defined as zero labor income. The vertical lines denote 95% confidence intervals based on standard errors clustered at the establishment level.

Figure A13: Change in worker quality of target establishments around mergers



Notes: The figure shows regression coefficients and associated confidence intervals for the difference between treatment and comparison group in a given year τ relative to the year of acquisition in the treatment group establishments, i.e., the δ_τ from the difference-in-differences model in (4). The coefficient in $\tau = -1$ is normalized to zero. Regressions are weighted by average establishment employment between $\tau = -3$ and $\tau = -1$. The outcome variable is average worker quality measured by average worker fixed effects, where worker fixed effects are estimated from AKM-type regressions with worker fixed effects and establishment fixed effects. The vertical lines denote 95% confidence intervals based on standard errors clustered at the establishment level.

Figure A14: Wage effects of failed mergers

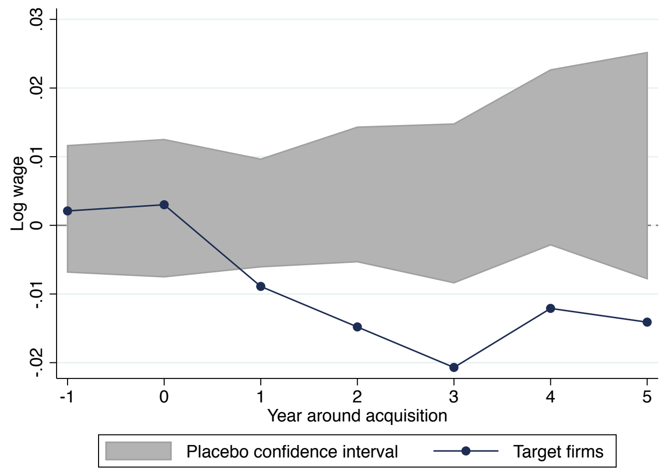


(a) Staying workers

(b) All initially employed workers

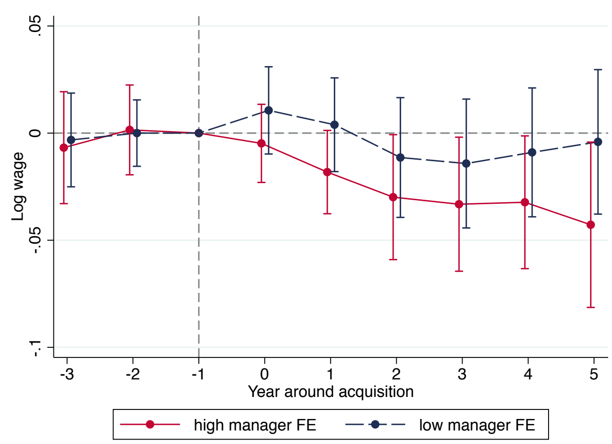
Notes: The figure shows regression coefficients and 95% confidence intervals for the difference between wages at failed target and control establishments. We match 365 targets of failed mergers from SDC Platinum to the administrative register data. We then match each failed target establishment to a control establishment using the same procedure in Section 4.1. The left figure plots wage effects for staying workers, i.e. δ_τ in equation (5); the right figure plots wage effects for all initially employed workers.

Figure A15: Synthetic control



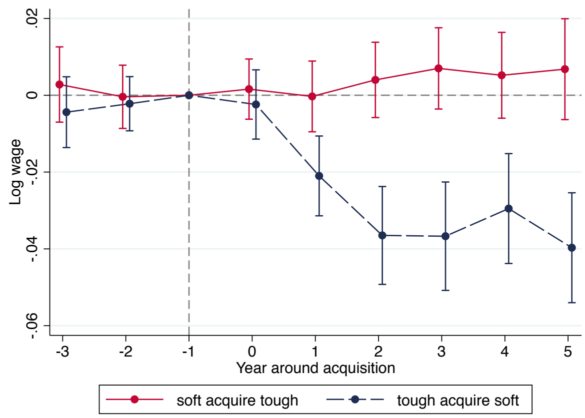
Notes: This figure shows the estimate of the effects of M&As on target establishments' earnings per worker using synthetic control. The shaded area is the [2.5, 97.5] confidence interval constructed using placebo treatment groups. See Appendix 2.1.2 for details.

Figure A16: Heterogeneity of wage effects by manager FE: split-sample IV estimates



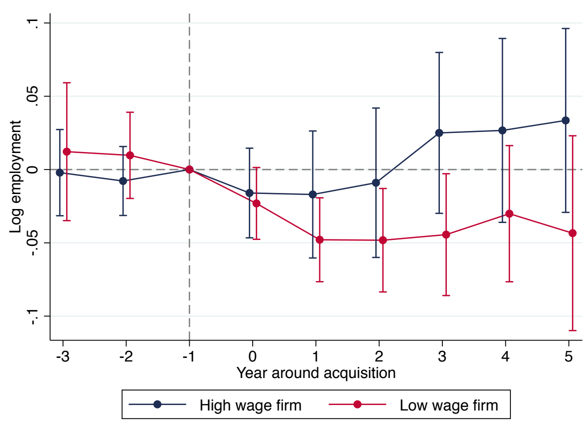
Notes: The figure shows regression coefficients and associated 95% confidence intervals for the difference between staying workers at target and control establishments separately by target establishments' manager FE. The sample is divided evenly by odd and even years and manager FE is estimated for each subsample. Manager FEs in odd years are instrumented with the manager FEs in even years and vice versa.

Figure A17: Effects of mergers on wages based on difference in manager FE between acquirer and target



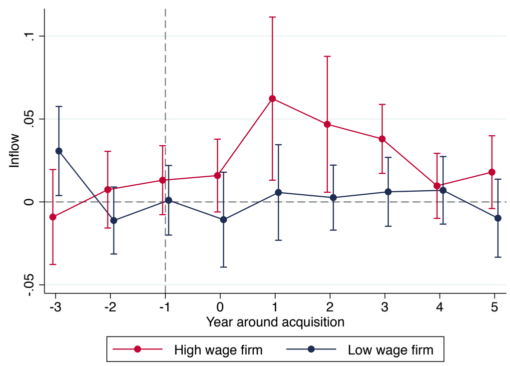
Notes: The figure shows regression coefficients and associated 95% confidence intervals for the difference between staying workers at target and corresponding control establishments. The treatment establishments are re-matched to control establishments such that they are in the same quartile of manager fixed effects. The red (navy) line contains target establishments with manager fixed effect lower (higher) than the manager fixed effect of its acquirer firm and the corresponding control establishments. Standard errors are clustered at the establishment level.

Figure A18: Effects of mergers on employment at high wage and low wage target establishments

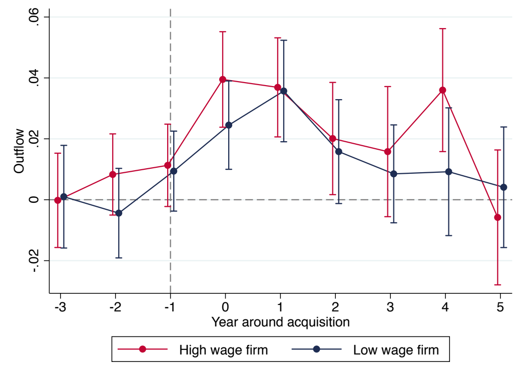


Notes: The figure shows regression coefficients and associated 95% confidence intervals for the difference between log employment at target and corresponding control establishments separately by target establishments' pre-merger wage residual. Inflow (outflow) at year τ is calculated as the number of entrants (leavers) between year $\tau-1$ and year τ divided by employment in year $\tau-1$. The treatment establishments are re-matched to control establishments such that they are in the same quartile of wage residual. The regression includes establishment fixed effects and year fixed effects. The coefficient in $\tau=-1$ is normalized to zero. High wage establishments are establishments with above-median wage residual in the year before merger, where the residual is from regressing establishment-year fixed effects on productivity and industry-year and region-year fixed effects. The wage residual proxies for manager softness. Standard errors are clustered at the establishment level.

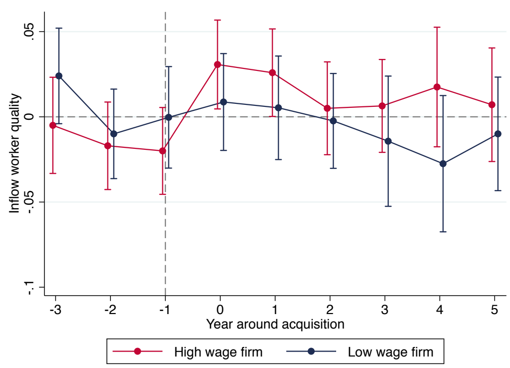
Figure A19: Inflow and outflow at high wage and low wage target establishments



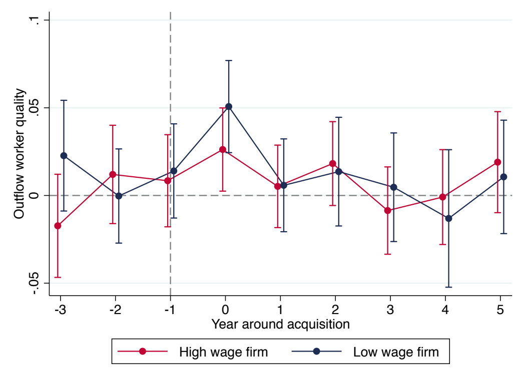
(a) Inflow



(b) Outflow



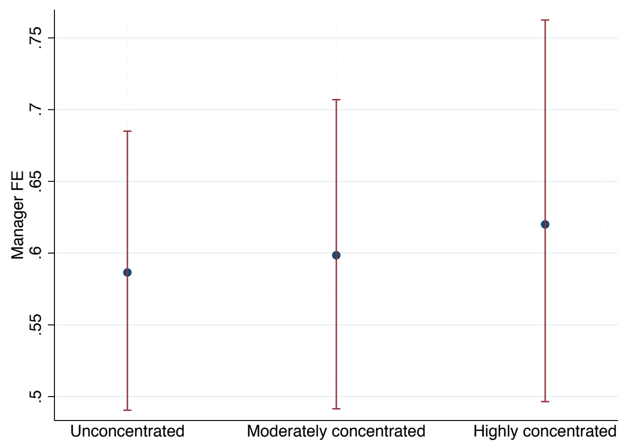
(c) Inflow Worker Quality



(d) Outflow Worker Quality

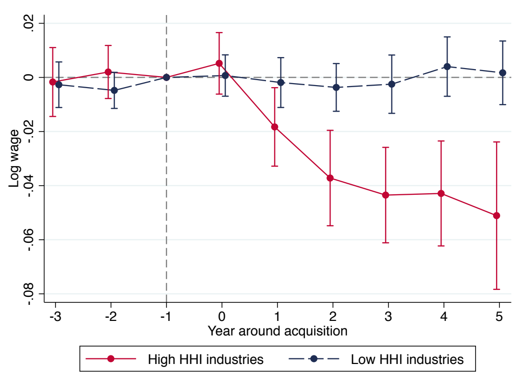
Notes: The figure shows regression coefficients and associated 95% confidence intervals for the difference between job inflows and outflows at target and corresponding control establishments separately by target establishments' pre-merger wage residual. Inflow (outflow) at year τ is calculated as the number of entrants (leavers) between year $\tau-1$ and year τ divided by employment in year $\tau-1$. Worker quality of inflow (outflow) at year τ is calculated as the average person fixed effects (estimated in step 1 of Section 3.1) of entrants (leavers) between year $\tau-1$ and year τ divided by employment in year $\tau-1$. The treatment establishments are re-matched to control establishments such that they are in the same quartile of wage residual. The regression includes industry by year fixed effects. High wage establishments are establishments with above-median wage residual in the year before merger, where the residual is from regressing establishment-year fixed effects on productivity and industry-year and region-year fixed effects. The wage residual proxies for manager softness. Standard errors are clustered at the establishment level.

Figure A20: Industry Concentration and Manager Fixed Effects

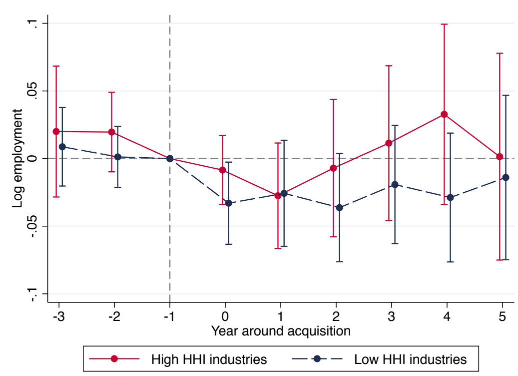


Notes: The figure plots the distribution of manager fixed effects in wage setting in industries with different levels of concentration. The dots are median manager fixed effecs for each industry group, and the vertical bars denote the range from 25th percentile to 75th percentile of manager fixed effects for each industry group. Three-digit industries are defined as unconcentrated if its HHI is less than 1,500; moderately concentrated if HHI is between 1,500 and 2,500; and highly concentrated if HHI is above 2,500 (according to the Horizontal Merger Guidelines). Manager fixed effects measure managers' generosity in wage setting and the estimation is detailed in Section 4.1.

Figure A21: Heterogeneity by industry concentration



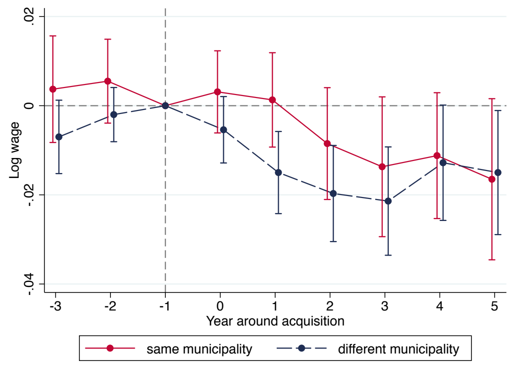
(a) Wage



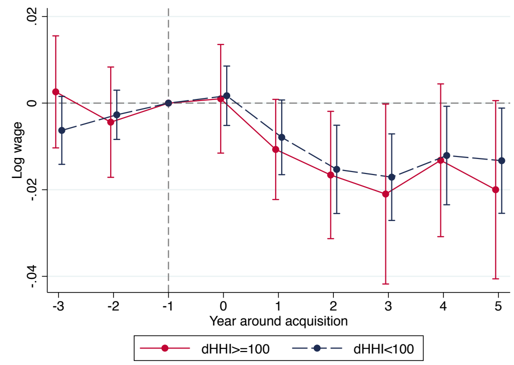
(b) Employment

Notes: The figure shows regression coefficients and associated confidence intervals for the difference between wages of staying workers and employment at target and corresponding control establishments in high concentration and low concentration industries. There are 127 three-digit industries and concentration is defined by the Herfindahl-Hirschman index. High concentration industries have HHI above 1000. The left figure plots coefficients δ_τ from the worker-level difference-in-differences model in (5), and the right figure plots coefficients δ_τ from the establishment-level difference-in-differences model in (4). The coefficient in $\tau = -1$ is normalized to zero. The vertical lines denote 95% confidence intervals based on standard errors clustered at the establishment level.

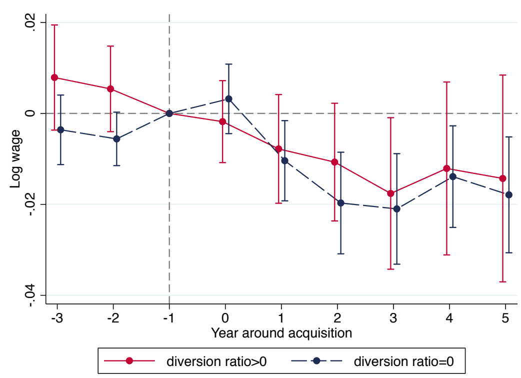
Figure A22: Testing Monopsony



(a) Local labor market by municipality



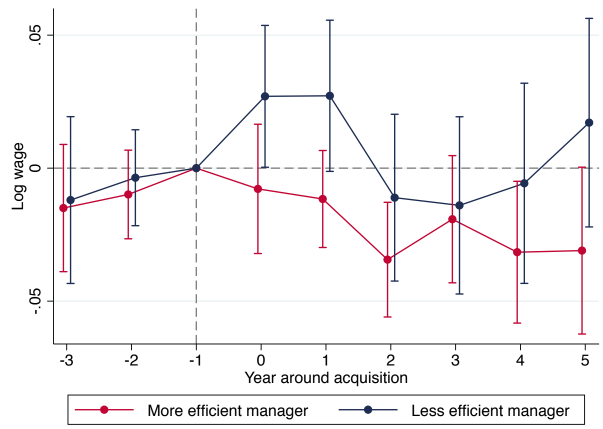
(b) Labor market by occupation and region



(c) Diversion ratio

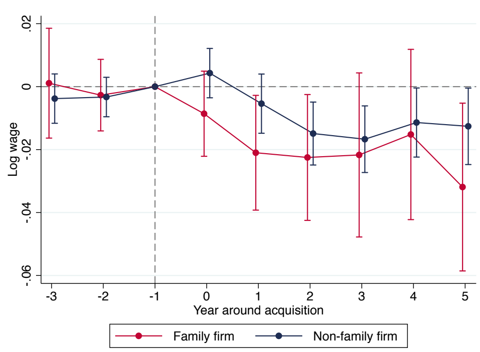
Notes: This figure tests whether negative wage effects of mergers are due to increased monopsony power in the labor market. Each figure plots the regression coefficients and associated 95% confidence intervals for the difference between staying workers at target and corresponding control establishments separately for mergers that have larger or smaller impact on monopsony power. In (a), monopsony power is calculated by concentration in the local labor markets defined by municipalities, and red (blue) line contains target establishments which are in same (or different) municipality as the acquirer and their correponding control establishments. In (b), monopsony power is calculated by concentration in the local labor markets defined by geographical region (similar to commuting zones) and 4-digit occupation, and red (blue) line contains mergers that increased the labor market HHI by more (or less) than 100 points. In (c), monopsony power is calculated by the diversion ratio, which is measured by the fraction of job movers from target firms that move to the acquirer firm in the years before merger. Red (blue) line contains target establishments with positive (or zero) diversion ratios and their correponding control establishments. Standard errors are clustered at the establishment level.

Figure A23: Manager productivity and effects of mergers on wages

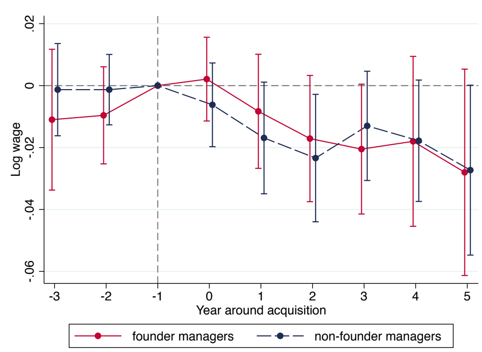


Notes: The figure shows regression coefficients and associated 95% confidence intervals for the difference between staying workers at target and corresponding control establishments separately by target establishments' pre-merger manager productivity. Manager productivity is estimated using equation (2) with TFP on the left hand side. The red (navy) line includes target establishments with above-median (below-median) manager productivity and their corresponding control establishments. Standard errors are clustered at the establishment level.

Figure A24: Manager ownership and effects of M&As on wages



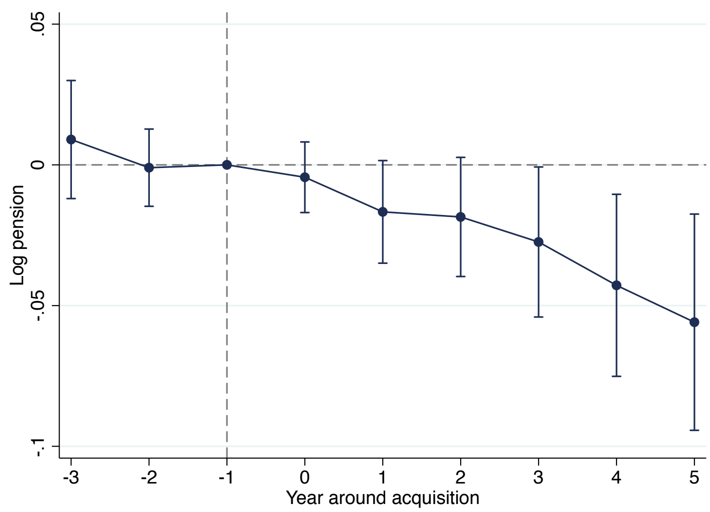
(a) Family firm



(b) Founder

Notes: The figure shows regression coefficients and associated 95% confidence intervals for the difference between staying workers at target and corresponding control establishments, for family firms and non-family firms in (a), and for firms with founder and non-founder managers in (b). We define family firms following Bennedsen et al. (2007) and a firm is a family firm if managers in different years are family members. A manager is a founder if the manager worked at the firm in the first year the firm existed.

Figure A25: Effects of mergers on pensions of target employees



Notes: The figure shows regression coefficients and associated confidence intervals for the difference between log pension payments of staying workers at target and control establishments, i.e., the δ_τ from the difference-in-differences model in (5). The coefficient in $\tau = -1$ is normalized to zero. The vertical lines denote 95% confidence intervals based on standard errors clustered at the establishment level.

Table A1 Characteristics of Treated and Control Establishments

Variables	Treated Establishments	Control Establishments
Median employment	11	11
Mean employment	25.0	22.8
Log hourly wage	5.002	4.987
Log annual income	12.131	12.126
Log employment growth from previous year	-0.009	-0.007
Log wage growth from previous year	0.021	0.025
Share of workers with higher education	0.184	0.202
Share of workers with vocational education	0.418	0.407
Share of female workers	0.468	0.512
Average worker age	38.74	38.64
Average worker experience	15.22	15.30
Log Value added per worker	6.048	6.054
Log Sales per worker	7.218	7.197
Establishment age	14.79	15.44
Number of establishments	5,875	5,875

Notes: This table presents summary statistics for all target establishments and control establishments. Each target establishment is matched to a control establishment using the matching approach detailed in Section 4.1. All the characteristics are calculated at one year before the merger occurs, and wage and employment growth is the growth rate from two years before the merger to one year before the merger. The medians are calculated as the average value of 10 observations around the median.

Table A2 Effects of Mergers on Worker Departure

	Dependent Variable: Departure Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
	All workers	Wage Quartile 1	Wage Quartile 2	Wage Quartile 3	Wage Quartile 4	Managers
Year t=0	0.011	0.006	0.009	0.007	0.025	0.030
	(0.008)	(0.017)	(0.010)	(0.007)	(0.008)	(0.007)
Year t=1	0.008	0.004	0.003	0.004	0.019	0.052
	(0.015)	(0.026)	(0.019)	(0.005)	(0.016)	(0.011)
Year t=2	0.014	0.001	0.002	0.007	0.026	0.071
	(0.016)	(0.026)	(0.021)	(0.007)	(0.018)	(0.013)
Year t=3	0.010	0.003	0.006	0.005	0.020	0.070
	(0.017)	(0.028)	(0.023)	(0.019)	(0.020)	(0.013)
Year t=4	0.005	0.002	0.006	0.000	0.007	0.066
	(0.018)	(0.028)	(0.024)	(0.020)	(0.022)	(0.014)
Year t=5	0.003	-0.007	0.008	-0.001	0.010	0.063
	(0.020)	(0.028)	(0.026)	(0.020)	(0.025)	(0.016)
No. of observations	1,121,850	278,339	277,318	282,790	283,233	50,534

Notes: This table shows the effect of mergers on probability of leaving for workers in target establishments. The dependent variable is a dummy variable that equals one if the worker is not in the same establishment as in year -1 (the year before merger), and the coefficients are δ_τ in the difference-in-differences regression (6) in the Appendix. All regressions control for person fixed effects and year fixed effects. The wage quartile of a worker is calculated at year $\tau = -1$ compared to all other workers in that year, and wage quartile 1 is the lowest wage quartile. Managers are defined using occupation codes (see Data Appendix for details) and each establishment has one manager in each year. Standard errors are clustered by establishment and reported in parentheses.

Table A3 Wage Effects on Stayers: Alternative Matching Strategies

	Dependent Variable: Log Wage					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	No spillover	Match at year -2	Two controls per firm	Non-parametric: Target	Non-parametric: Control
Year t= -5	0.0002	0.0001	-0.0003	-0.0009	-0.0029	-0.0001
	(0.0056)	(0.0051)	(0.0061)	(0.0057)	(0.0027)	(0.0026)
Year t= -4	0.0001	-0.0014	0.0039	0.0041	-0.0020	0.0031
	(0.0037)	(0.0037)	(0.0046)	(0.0048)	(0.0020)	(0.0020)
Year t= -3	-0.0045	-0.0021	-0.0035	0.0017	-0.0006	-0.0030
	(0.0035)	(0.0036)	(0.0040)	(0.0044)	(0.0017)	(0.0019)
Year t= -2	-0.0030	-0.0040	-0.0047	0.0013	0.0003	0.0025
	(0.0028)	(0.0028)	(0.0031)	(0.0039)	(0.0015)	(0.0017)
Year t= 0	0.0018	-0.0007	-0.0055	-0.0015	0.0007	0.0050
	(0.0033)	(0.0035)	(0.0039)	(0.0030)	(0.0019)	(0.0016)
Year t= 1	-0.0077	-0.0110	-0.0117	-0.0081	-0.0062	0.0031
	(0.0040)	(0.0040)	(0.0042)	(0.0036)	(0.0019)	(0.0018)
Year t= 2	-0.0153	-0.0170	-0.0135	-0.0144	-0.0112	-0.0025
	(0.0043)	(0.0043)	(0.0043)	(0.0046)	(0.0022)	(0.0020)
Year t= 3	-0.0157	-0.0149	-0.0167	-0.0182	-0.0119	-0.0019
	(0.0049)	(0.0045)	(0.0057)	(0.0055)	(0.0024)	(0.0021)
Year t= 4	-0.0100	-0.0111	-0.0072	-0.0094	-0.0118	-0.0029
	(0.0051)	(0.0047)	(0.0063)	(0.0057)	(0.0027)	(0.0023)
Year t= 5	-0.0139	-0.0068	-0.0185	-0.0125	-0.0049	0.0009
	(0.0059)	(0.0051)	(0.0071)	(0.0063)	(0.0029)	(0.0026)
No. of observations	1,350,387	1,310,042	1,120,943	1,902,474	24,987,697	24,950,534

Notes: This table shows the effect of mergers on wages of staying workers in target establishments from year -5 to year 5 relative to the merger (coefficients δ_τ in regression (5)). All regressions control for person fixed effects and year fixed effects. Column 1 is our baseline specification. Column 2 selects control establishments that have similar propensity score and wage and employment levels but are in different industry and different geographical region from the treated establishments. Column 3 matched treated establishments to controls based on covariates at year -2 instead of year -1. In Column 4 we choose two establishments as control for each target establishment based on the propensity score. Column 5 and Column 6 use the non-parametric estimator as in Davis et al. (2014) (see Appendix 2.1.1 for details). Column 5 shows the wage effects for target establishments, and Column 6 shows the wage effects for control establishments of the baseline propensity score matching as a placebo test. Standard errors are clustered by establishment and reported in parentheses.