

## **Online Appendices**

## Online Appendix A: Assessing the Bias from Measurement Error in Nonprofit Status

To explore the direction of the bias arising from measurement error, we present an omitted-variable framework with one regressor and one omitted variable. We assume for simplicity that the measurement error is not correlated with other regressors. Let  $NP$  equal 1 if a worker's employer is a nonprofit firm and 0 otherwise. We introduce measurement error through the variable  $V$  which can take on three values ( $-1$ ,  $1$ , and  $0$ ), mapping to the three reporting scenarios. If an employee correctly reports the tax status of his firm,  $V$  equals 0. If an employee incorrectly identifies his nonprofit employer as a for-profit firm,  $V$  equals  $-1$ . Conversely, if the employee of a for-profit firm mistakenly reports he works for a nonprofit firm,  $V$  equals 1. Note that  $cov(NP_i, V_i) \leq 0$ , since  $NP$  is a binary variable.

We are interested in estimating the parameter  $\beta_1$ , the wage differential associated with nonprofit work from a regression model:

$$y_i = \beta_0 + \beta_1 NP_i + \epsilon_i$$

In survey records,  $NP$  is measured with error, which measurement we call  $\widetilde{NP}$ :

$$\widetilde{NP}_i = NP_i + V_i$$

A linear regression using the noisy measure of firm nonprofit status will yield parameter  $\beta_1^*$ , the expectation of which reveals two sources of bias:

$$E[\hat{\beta}_1^*] = \frac{cov(Y_i, NP_i)}{var(NP_i + V_i)} + \frac{cov(Y_i, V_i)}{var(NP_i + V_i)}$$

If the measurement error is uncorrelated with wages, then the second term is zero and the bias reduces to a simple case in which the estimated coefficient can either be inflated or attenuated, depending on the magnitude of  $var(NP_i + V_i)$  compared to  $var(NP_i)$ . Without additional

information about the probability of misreporting, it is unclear whether the coefficient would be attenuated or inflated.

In the more complex case,  $V_i$  is also correlated to wages which introduces additional bias. For example, imagine that high-wage nonprofit workers tend to identify their employer as a for-profit because they assume that only for-profit organizations can afford their high salary. The correlation between wages and measurement error is negative—when wages are high,  $V_i$  is more likely to be  $-1$ . In this scenario, the estimated  $\hat{\beta}_1^*$  would not only have an attenuation or inflation bias, but a negative bias as well. If the measurement error is severe, the sign on the estimated  $\hat{\beta}_1^*$  present estimates opposite of true  $\beta$ .<sup>1</sup>

With few exceptions, previous studies on nonprofit workers use self-reported measures to determine a firm's nonprofit status. To illustrate the potential scope of the measurement problem, we tally the within-industry gaps between true nonprofit share and self-reported nonprofit share. Table 1 reports the percentage point difference between the reported nonprofit share in the ACS and the actual nonprofit share in our administrative records. A negative percentage point error indicates that in the ACS a smaller share of an industry's workers reported their employer is a nonprofit firm than the actual share of nonprofit workers indicated in administrative records. In the ACS, the hospital industry has a large share of nonprofit workers reporting they are working at a for-profit hospital. Religious and Civic organizations have "missing" for-profit workers who mistakenly report their employer as a nonprofit. These two industries have the largest reporting errors by far, with significant misreporting in other industries including education. Multiplying the percentage point error by the industry's share of total workers in the economy and summing across all industries gives us a lower bound estimate that 4 percent of all workers are misreporting their

nonprofit status. Since the true nonprofit share in Florida is approximately 8 percent, this represents a significant scope for error.

### **Online Appendix B: Decomposing Nonprofit Earnings Penalty**

Among industries evincing a nonprofit premium, there are three traits that differentiate nonprofit and for-profit firms that may explain the premium, and, in this section, we develop a simple model and explore data that allow us to attribute wage differences to the component dissimilarities between the two sectors. We show formally that wage differences can be explained by differences in productivity, taxation, and the non-distribution constraint found in nonprofits.

The primary legal difference between nonprofits and other firms is that nonprofits operate under a non-distribution constraint which forbids them from disbursing their excess revenues (i.e. profits) to owners or managers of the firm. This constraint may induce firms to pay workers more since excess revenues must be reinvested in the firm. Related, nonprofits also differ from traditional firms in that they are not subject to income taxes.

With respect to productivity, for-profits incentivize productivity to the extent it maximizes profits. Nonprofit organizations are not intended to share this motive. Productivity may also differ in nonprofits if they have different cultural values and priorities. For instance, if those who select into nonprofit work have a high value on priorities that do not directly increase productivity, these cultural influences may have an independent effect on productivity; on the other side, workers in nonprofits may have higher intrinsic motivation to accomplish the nonprofits' goals, generating

more sustained effort; or, the presence of superordinate goals may improve relations among workers to yield higher productivity (Sherif 1958).

To decompose the component parts, consider two firms of the equal employment in the same industry: one is a nonprofit and the other is a for-profit. The for-profit firm generates profits of the form:

$$\Pi = (1 - \mathbf{t})\{p\phi(L, K) - cK - wL\}$$

For simplicity we assume that  $K$  is fixed, being determined by the firm's industry standard and total employment, which are equivalent. By rearranging terms, we learn the identity that determines worker wages. Thus, the worker wage is represented by:

$$w_{fp} = \frac{p\phi(\bar{L}, \bar{K})}{\bar{L}} - \frac{\tilde{c}\bar{K}}{\bar{L}} - \frac{\Pi}{(1 - \mathbf{t})\bar{L}}$$

In words, the wages of a for-profit worker are a function of per-capita productivity, costs, taxes, and residual profits.

Nonprofits have a similar identity for their net earnings. Here  $w$  is the market wage.

Nonprofits may pay above or below market wage depending on whether their workers donate labor or receive rents from any excess revenues.

$$E = p'\eta(L, K) - cK - (w - \delta + r)L \mid E = 0$$

Defining  $w_{np} = w - \delta + r$ , as the wage paid to nonprofit workers, we can write the wages of a nonprofit worker as:

$$w_{np} = \frac{p'\eta(\bar{L}, \bar{K})}{\bar{L}} - \frac{\tilde{c}\bar{K}}{\bar{L}} - \frac{E}{\bar{L}}$$

Put simply, nonprofit wages are also a function of per-person productivity and costs. For clarity, we have included excess revenues in the wage equation, although by assumption it is zero. By including it, we can see that setting excess revenues equal to zero can only increase the wages of a nonprofit

worker in contrast to if the firm was allowed profits. In nonprofits, excess revenues are eventually reinvested in the firm and so there are no excess revenues and the firm owes no taxes. We assume that the cost of capital  $c$  is common across sectors, being rented at a market rate. Thus, the important distinctions that give rise to differences in nonprofit and for-profit wages are productivity (the wedge between  $\phi$  and  $\eta$ ), the non-distribution constraint ( $\mathbf{E}$ ), and corporate taxation ( $\mathbf{t}$ ).

Using both wage identities, the wage gap is defined as:

$$w_{np} - w_{fp} = \left( \frac{\mathbf{p}'\boldsymbol{\eta}(\bar{L}, \bar{K})}{\bar{L}} - \frac{\mathbf{p}\boldsymbol{\phi}(\bar{L}, \bar{K})}{\bar{L}} \right) + \frac{\Pi}{(\mathbf{1} - \mathbf{t})\bar{L}}$$

In this gap equation, the non-distribution constraint surfaces as the penalties for-profit workers face that are not present for nonprofit workers, namely lower wages correlated to higher profits and higher taxes. Thus, the wage gap is a product of a productivity gap and the non-distribution constraint, which come together additively. If, for instance, we find that there is a 10 percent wage gap in favor of nonprofits and nonprofits are 6 percent more productive than their for-profit peers, then the remaining gap to be explained is 4 percent to be explained by the non-distribution constraint. The amount of income available for rent sharing with workers, however, is enlarged by the tax treatment of nonprofits. That is, since nonprofits are spared the 25% average tax rate firms normally pay, a quarter of the earning difference between nonprofits and for profits is attributable to the tax and the remaining three quarters is attributable to the non-distribution constraint without the tax's influence. Thus, in our example, a quarter of the difference (1 percent), we attribute to the tax relief and the remaining three-quarters of the

difference (3 percent) we attribute to the non-distribution constraint. We apply this model to commercial banking and to the hospitals.

### Online Appendix C: Local Labor Market Competition

One possible explanation for the varying nonprofit penalties across industries is that a higher level of labor-market competition in some industries drives nonprofits to pay a higher premium. We examine the difference between wages of workers at nonprofit and for-profit outpatient health centers across counties. We focus on outpatient healthcare centers because the industry has a near-zero wage differential, it has a large number of for-profit and nonprofit workers, and the services provided by both types of firms in the industry is identical.

Our measure of local labor market competition between for profit and nonprofit firms is the share of outpatient health care workers in county  $j$  in year  $y$ , that work for a nonprofit.

$$C_j = \frac{(total\ nonprofit\ employment)_{jy}}{(total\ nonprofit\ employment)_{jy} + (total\ for - profit\ employment)_{jy}}$$

We run the following regression to determine if the nonprofit differential varies across counties with differing shares of nonprofit workers, denoting  $W_{iste}$  the log-wage of individual  $i$ , in year-quarter  $s$ , at event time  $t$ .

$$W_{iste} = \beta_1 NP_{iste} + \beta_2 NP_{iste} \times C_{j(i,y)} + \Gamma_s + \theta_t + \gamma_e + \varepsilon_{iste}$$

We include year and quarter controls, event time controls, and event fixed effects. The variable of interest is the coefficient on the interaction term of the nonprofit tax status and the share of outpatient healthcare workers that work at a nonprofit.

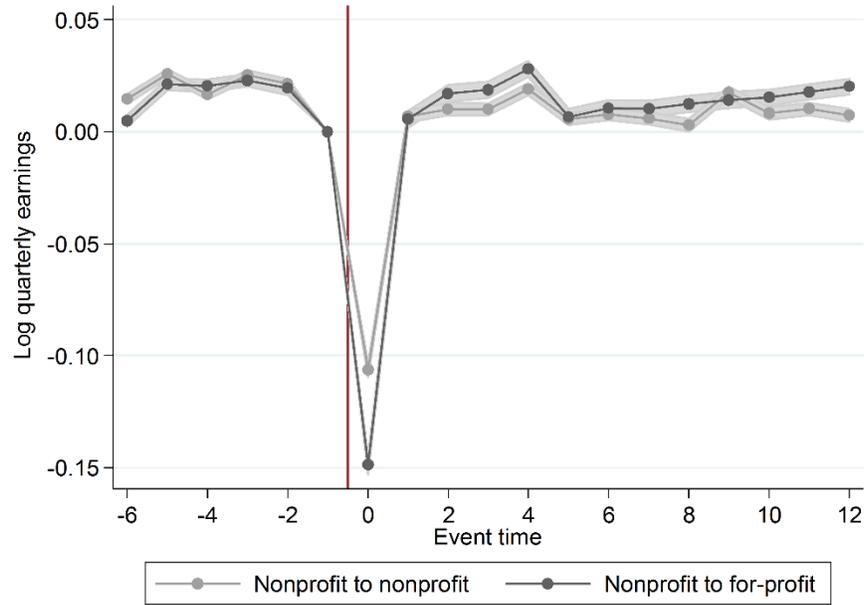
In addition to using share of workers as a measure of competitiveness, we also use the number of firms in each county. Online Appendix table 3 presents these results. In both cases the coefficient on the interaction terms are small and insignificant, suggesting that local labor market competition is not driving differences in the nonprofit differential for outpatient health care

centers. Since industries with a near-zero wage differential are similar to the outpatient healthcare industry in important ways, including employing large numbers of for-profit and nonprofit workers, and providing similar services across for-profit and nonprofit firms, one can suppose that results would be similar in those cases as well.

Online Appendix E: Supplemental Figures

Online Appendix Figure 1:

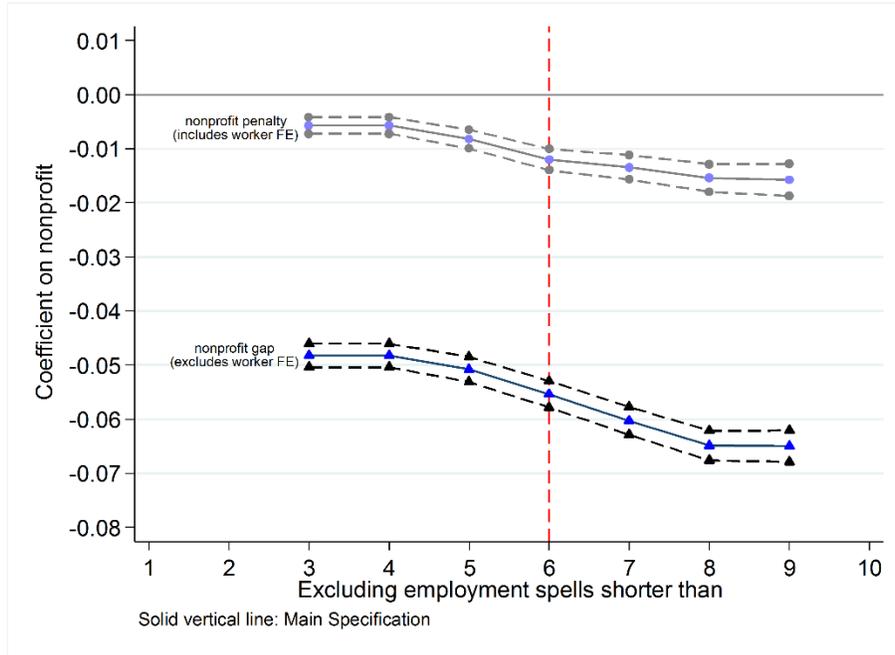
Event Study – Job Changes from Nonprofit Employers



Note: We plot the event-time dummies for workers who changed jobs between 2003-2012 and held the previous job and the new job for at least six quarters (eighteen months). After  $t=6$ , the results derive from an unbalanced panel. Controls include a full set of event-time dummies, year-quarter dummies, and event dummies.

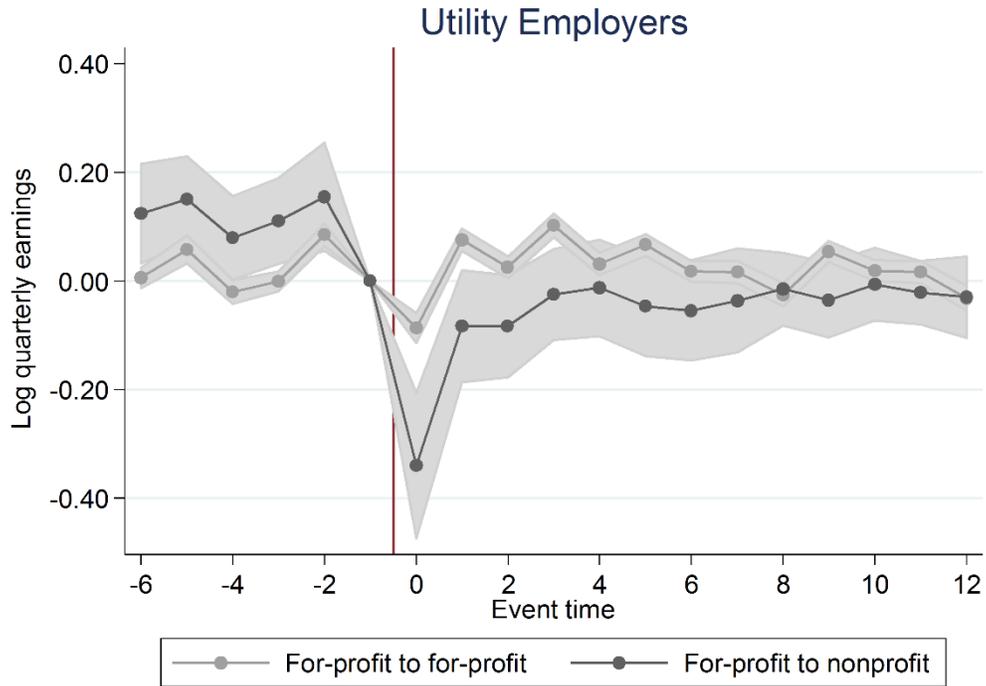
Online Appendix Figure 2:

Sensitivity to Employment-Spell-Duration Exclusion



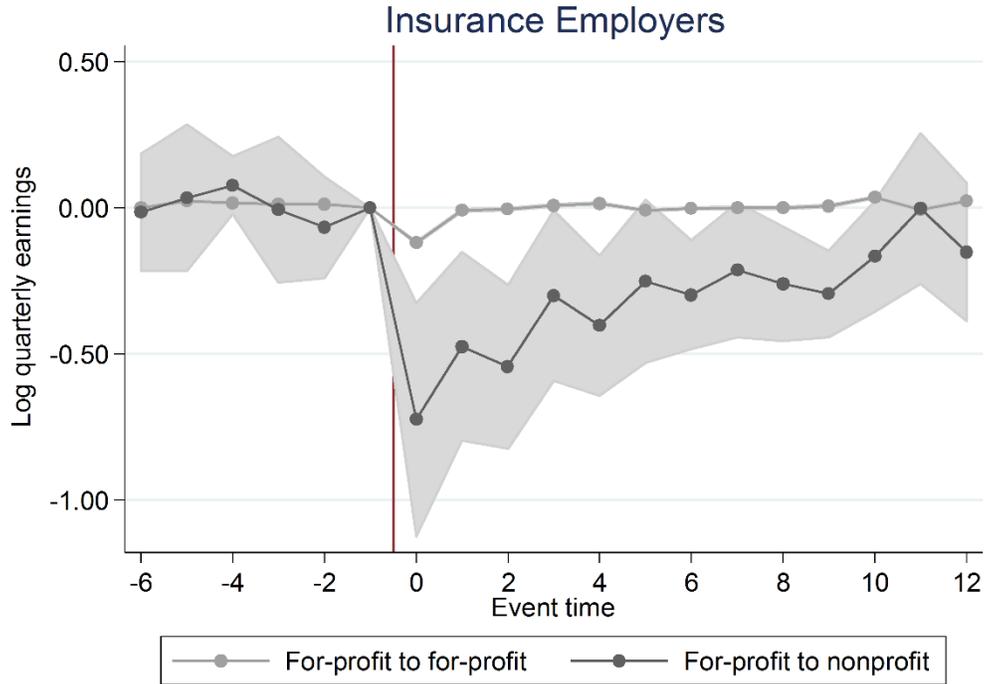
Note: We plot the nonprofit coefficients from columns (3) and (4) in table 3 while varying the duration of employment excluded from the analytic sample.

Online Appendix Figure 3:  
Event Study among Utilities Movers



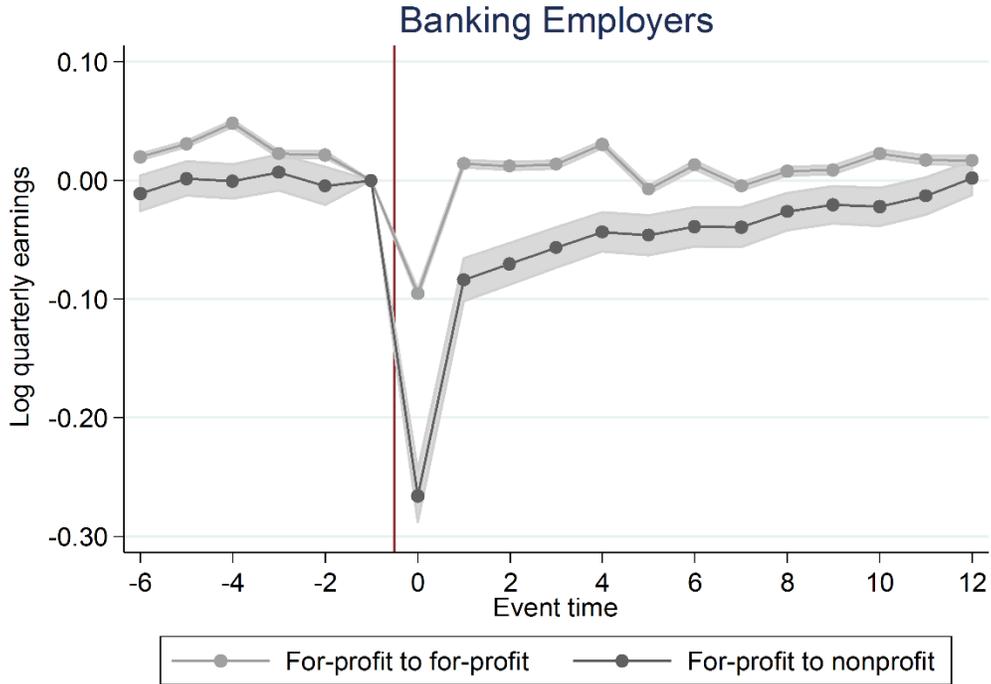
Note: Figure shows the coefficients  $\alpha_i^q$  in equation (1) for two event-types: a move from a for-profit to a nonprofit (which we refer to as the treatment group) and a move from a for-profit to a for-profit firm (which we refer to as the control group) for the utilities industry. The dependent variable is log quarterly wages. The event-time dummy at  $t = -1$  is omitted. Industry classification is determined by 3-digit NAICS codes. The grey, shaded areas bounding each line represent the 95 percent confidence interval.

Online Appendix Figure 4:  
Event Study for Insurance Movers



Note: Figure shows the coefficients  $\alpha_j^q$  in equation (1) for two event-types: a move from a for-profit to a nonprofit (which we refer to as the treatment group) and a move from a for-profit to a for-profit firm (which we refer to as the control group) for the insurance industry. The dependent variable is log quarterly wages. The event-time dummy at  $t = -1$  is omitted. Industry classification is determined by 3-digit NAICS codes. The grey, shaded areas bounding each line represent the 95 percent confidence interval.

Online Appendix Figure 5:  
Event Study for Banking and Credit Movers



*Note:* Figure shows the coefficients  $\alpha_j^q$  in equation (1) for two event-types: a move from a for-profit to a nonprofit (which we refer to as the treatment group) and a move from a for-profit to a for-profit firm (which we refer to as the control group) for the banking and credit industry. The dependent variable is log quarterly wages. The event-time dummy at  $t = -1$  is omitted. Industry classification is determined by 3-digit NAICS codes. The grey, shaded areas bounding each line represent the 95 percent confidence interval.

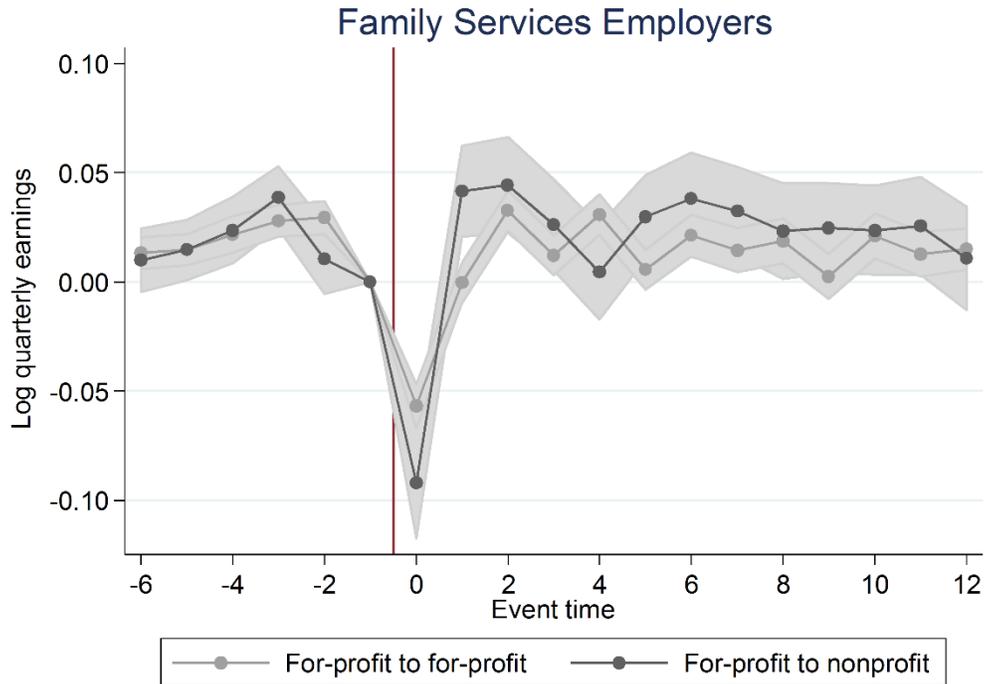


Online Appendix Figure 6:  
Event Study for Hospital Movers



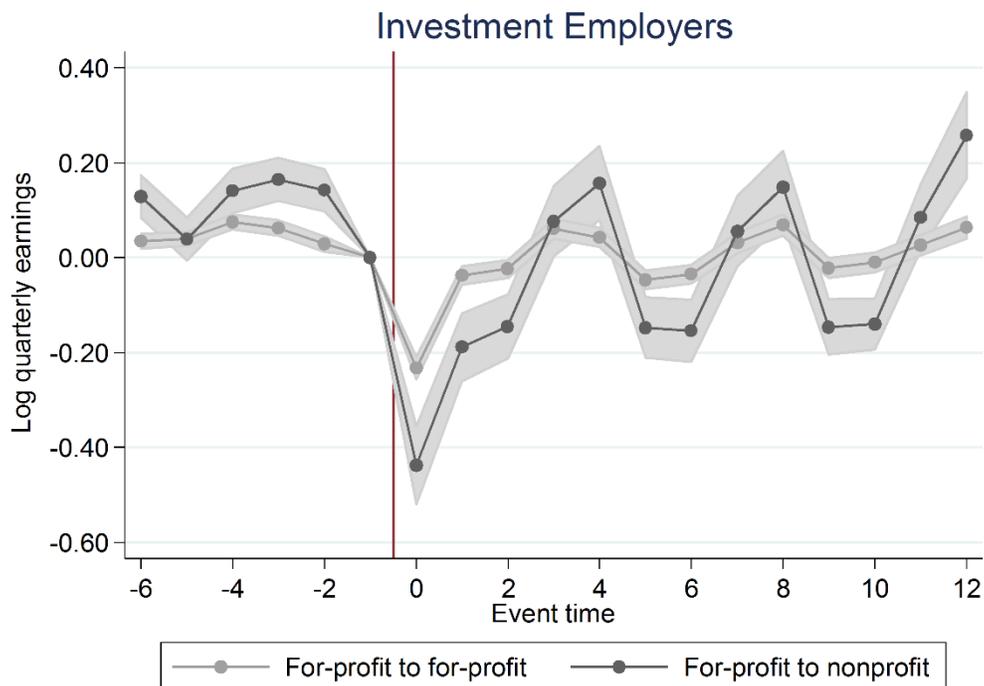
Note: Figure shows the coefficients  $\alpha_j^q$  in equation (1) for two event-types: a move from a for-profit to a nonprofit (which we refer to as the treatment group) and a move from a for-profit to a for-profit firm (which we refer to as the control group) for the hospital industry. The dependent variable is log quarterly wages. The event-time dummy at  $t = -1$  is omitted. Industry classification is determined by 3-digit NAICS codes. The grey, shaded areas bounding each line represent the 95 percent confidence interval.

Online Appendix Figure 7:  
Event Study for Family Services Movers



Note: Figure shows the coefficients  $\alpha_t^q$  in equation (1) for two event-types: a move from a for-profit to a nonprofit (which we refer to as the treatment group) and a move from a for-profit to a for-profit firm (which we refer to as the control group) for the family services industry. The dependent variable is log quarterly wages. The event-time dummy at  $t = -1$  is omitted. Industry classification is determined by 3-digit NAICS codes. The grey, shaded areas bounding each line represent the 95 percent confidence interval.

Online Appendix Figure 8:  
Event Study for Investment Movers



*Note:* Figure shows the coefficients  $\alpha_j^q$  in equation (1) for two event-types: a move from a for-profit to a nonprofit (which we refer to as the treatment group) and a move from a for-profit to a for-profit firm (which we refer to as the control group) for the investment industry. The dependent variable is log quarterly wages. The event-time dummy at  $t = -1$  is omitted. Industry classification is determined by 3-digit NAICS codes. The grey, shaded areas bounding each line represent the 95 percent confidence interval.



Online Appendix E: Supplemental Tables

Table 1 : Types of Employers in Each Designation

	<u>Nonprofit</u> (1)	<u>For-Profit</u> (2)
Hospitals (622)	General hospitals, children's hospitals, Psychiatric hospitals, rehabilitation hospitals (such as for alcoholism), specialty hospitals (e.g., cancer hospitals)	General hospitals, children's hospitals, Psychiatric hospitals, rehabilitation hospitals (such as for alcoholism), specialty hospitals (e.g., cancer hospitals)
Education (611)	Elementary and secondary schools, junior colleges, universities, <i>professional schools, secretarial schools, computer training</i> , professional development, technical trade schools, exam prep and tutoring, educational support (career and vocational counselling)	Elementary and secondary schools, junior colleges, universities, professional development, technical trade schools, exam prep and tutoring, educational support (career and vocational counselling)
Family Services (624)	Adoption agencies, activity centers for disabled or elderly people, addiction self-help organizations, child day care services, vocational rehabilitation services, disaster relief services, shelters for domestic abuse, marriage counselling	Adoption agencies, activity centers for disabled or elderly people, addiction self-help organizations, child day care services, vocational rehabilitation services, disaster relief services, shelters for domestic abuse, marriage counselling
Nursing Facilities (623)	Convalescent homes, assisted living facilities, inpatient hospice, nursing homes, group homes, retirement communities	Convalescent homes, assisted living facilities, inpatient hospice, nursing homes, group homes, retirement communities
Outpatient Health Care (621)	Offices for physicians (freestanding medical centers, psychiatry, dentists, speech therapists), home health care agencies, physical therapy, occupational therapy, <i>offices of podiatry</i> , dialysis centers, medical diagnostic labs, diagnostic imaging centers, optometrists, outpatient surgical centers	Offices for physicians (freestanding medical centers, psychiatry, dentists, speech therapists), home health care agencies, physical therapy, occupational therapy, dialysis centers, medical diagnostic labs, diagnostic imaging centers, optometrists, outpatient surgical centers

Banking & Credit (522)	Commercial banking, <i>credit card issuing, sales financing (e.g., automobile finance companies), savings institutions, financial transaction processing, loan brokers, construction lending</i>	Credit unions, construction lending
Insurance (524)	insurance agencies and brokers, life insurance carriers, <i>direct property and casualty insurance carriers, direct health and medical insurance carriers</i>	insurance agencies and brokers, life insurance carriers
Investments (523)	Investment banking and securities dealing, securities brokerage, <i>portfolio management, investment advice, trust/custody activities</i>	Investment banking and securities dealing, securities brokerage
Religious Organizations (8131)		Churches, shrines, monasteries, synagogues, mosques, temples
Civic Organizations (8134)		Scouting, parent-teacher associations, automobile clubs, fraternal lodges, social clubs, veterans' organizations, ethnic associations, booster clubs, alumni associations, granges

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*Note:* Definitions for each industry are derived from the Bureau of Labor Statistics.

Online Appendix Table 2: Employment Duration Across Sectors

	<u>Job-Tenure Duration in Quarters</u>			
	(1)	(2)	(3)	(4)
Nonprofit	1.376*** (0.015)	1.401*** (0.015)	1.308*** (0.015)	1.138*** (0.027)
Year-quarter FE		X	X	X
County FE			X	X
Worker FE				X
Mean DV	12.7	12.7	12.7	12.7
R-squared	0.00	0.09	0.09	0.63
Observations	3,473,478	3,473,478	3,473,478	3,473,478

*Note:* Table shows differences in the average employment spell for nonprofit and for-profit firms across various industries. Industries are determined by 3-digit NAICS codes. Job duration is measured in number of quarters each worker remains at a given employer.

Online Appendix Table 3:  
Local Labor Market Competition

	<u>Log Wages</u>	
	(1)	(2)
Nonprofit	0.035*** (0.009)	0.032*** (0.009)
Nonprofit x Share np workers	-0.029 (0.018)	
Nonprofit x Number of Firms		0.000 (0.000)
Year-quarter FE	X	X
Worker FE	X	X
Mean DV		
R-squared	0.89	0.89
Observations	2,847,819	2,805,038