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# Commercialism and Pay in the Nonprofit Sector

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ABSTRACT

COMMERCIALISM AND PAY IN THE NONPROFIT SECTOR

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Studies on the nonprofit pay differential find that nonprofit workers in the child daycare industry earn more than comparable for-profit workers (Ben-Ner, Ren, & Paulson, 2011; Preston, 1988), whereas nonprofit lawyers earn less than lawyers in for-profit firms (Frank, 1996; Weisbrod, 1983). Are nonprofit daycare center workers less altruistic than for-profit daycare workers or nonprofit lawyers? What is the meaning of a positive or negative nonprofit pay differential from various studies? This dissertation reframes the sectoral pay differential question and examines whether there is a donative labor effect for nonprofit workers relative to the for-profit workers.

Current empirical studies examining one or several industries produce a range of conflicting results, which makes comparison impossible and becomes a barrier to understanding the nature and magnitude of the nonprofit wage differential. Is there a relationship between industries and the sectoral pay differential? I develop measures to explain the relationship between the industry and the variability of the cross-sectoral pay differential based on the literature of commercialism on the industry level.

Prevailing theories, including donative labor theory, attenuated property rights theory, compensating wage theory, and efficiency wage theory, predict different outcomes. It remains unanswered what is the relationship of these theories, and why the conflicting theories find support in various studies. I employ the multilevel modeling approach to integrate research questions on different levels in one model to examine hypotheses developed from theories on different levels.

In the dissertation, I use nationally representative datasets and apply multilevel random effects modeling to answer two important questions: (1) Do nonprofits pay differently? And (2) what is the effect of commercialism? My analysis finds support for seemingly contradictory theories. The dissertation establishes an exhaustive inventory of nonprofit pay differentials for industries and occupations. The findings leave food for thought. Altruism motivation leads to lower pay for nonprofit workers, but the industry and occupation effects mask this difference.

COMMERCIALISM AND PAY IN THE NONPROFIT SECTOR

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Public Policy in the Andrew Young School of Policy Studies of Georgia State University.

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## Chapter I. Introduction

The nonprofit sector plays an important role in the US economy. The number of organizations with tax-exempt status is around 1.56 million in 2015, and 1.09 million of them were public charity organizations (McKeever, 2018). The actual number of nonprofits in the US is unknown because religious congregations and organizations with less than $5,000 receipts are not required to register (McKeever, 2018). Although nonprofit employment is only a portion of the for-profit employment (Hirsch, Macpherson, & Preston, 2018), the growth of the nonprofit employment outpaced that of business and government (McKeever & Gaddy, 2017; Salamon & Newhouse, 2019). Nonprofits employed 10.2 percent of the private workforce, and a total of 639 billion dollars was paid as annual wage in the nonprofit sector in 2016 (Salamon & Newhouse, 2019). Healthcare is the largest nonprofit employer offering jobs to 55 percent of nonprofit workers, followed by 14 percent in education and 12 percent in social assistance areas (Salamon & Newhouse, 2019). Given the scale of nonprofit employment and its labor-intensive nature of services, compensation is an important avenue to understand the nonprofit sector.

The nonprofit pay differential relative to the for-profit sector signals whether nonprofits differ from the for-profit sector in the aspect of human resources, that is, whether tax-exempt status is justified or nonprofits are just “for-profits in disguise” (Weisbrod, 1988). The meaningfulness of the topic intrigued extensive studies. However, the findings are inconclusive. Using administrative data with no control of individual information, Salamon and Newhouse (2019) find that nonprofits pay higher weekly wages than for-profits in nonprofit concentrate industries such as social assistance, education institutions, ambulance healthcare, hospitals, and nursing homes. Without control of human capital, it is hard to know whether the ostensible pay premium in the nonprofit sector reflects competitive and fair wage with the for-profit sector because many studies also find that nonprofit workers have more years of education and work experience, for instance.

Labor economists have proposed a series of theories in the 1980s predicting different outcomes in nonprofit wages. Donative labor theory predicts that nonprofit workers earn less than for-profit workers due to their altruistic motivation (Handy & Katz, 1998; Preston, 1989; Weisbrod, 1983). Attenuated property rights theorists that maintain nonprofit workers earn more than for-profit workers because nonprofit managers do not have the incentive to accumulate profits (Preston, 1988). Compensating wage theory proponents expect nonprofit workers to earn less than for-profit workers because the working conditions are better in nonprofits than the for-profits (Smith, 1979). Lastly, efficiency wage theory supports that firms pay more to increase the production of services if the work quality is hard to measure (Akerlof, 1984). Studies find negative nonprofit pay differentials, which provide support to donative labor theory (Handy, Mook, Ginieniewicz, & Quarter, 2007; Weisbrod, 1983). Others find that nonprofits pay equally or even slightly higher than for-profit firms, and thus conclude that there does not exist labor donation. Rather, it is the competition mechanism that works (Ben-Ner et al., 2011; Ruhm & Borkoski, 2003). The competition conclusion essentially rejects all theories that predict either positive or negative outcomes.

Findings from current studies are inconclusive, partly because they examine different industries (Preston, 1988) or occupations (King & Lewis, 2017; Weisbrod, 1983), or different mix of industries (Ben-Ner et al., 2011; Jones, 2015; Ruhm & Borkoski, 2003) and occupations (Frank, 1996; Handy et al., 2007), which makes it hard to compare the results. In an economy-wide study, Leete (2000) acknowledges that the overall pay parity is a sum of the significantly positive nonprofit differential in some industries and significantly negative differential in others.

A logical question to ask is why nonprofit workers are not the same. Presumably, they should be similar because they are all "nonprofit" workers. The question boils down to what makes a day-care center nonprofit worker differ from a hospital nonprofit worker, or what makes a lawyer nonprofit worker differ from a registered nurse nonprofit worker.

Conflicting findings send a mixed message concerning practical and policy implications. The answer is crucial to assure stakeholders who trust or distrust voluntary values. Nonprofit organizations are exempt from property, sales, and corporate income taxes (Hansmann, 1987). When nonprofit workers earn more than for-profit, it arouses concerns. On the one hand, if the nonprofit is not different from the for-profit sector, then the tax-exempt status puts nonprofits in an unfair competitive advantage over the for-profits. One the other hand, why nonprofits, without striving to make profits, can pay more than the for-profit sector. Do they distribute the surplus to owners and workers that are not allowed by law? It challenges the legitimacy of the sector (Salamon, 1999).

Conflicting findings make theories irrelevant. When findings on the nonprofit pay differential diverge and explanations depart from each other, we are left to wonder whether theories are wrong or whether there is poor correspondence between the theory and the concepts under study. "Nonprofit" might refer to altruistic motivation (donative labor theory), the lack of ownership of organizations (attenuated property rights theory), better working conditions (compensating wage theory), or less measurable production (efficiency wage theory). What is the referent for "nonprofit" in various studies?

The study of the sectoral pay differential needs to be situated in the overall backdrop, where nonprofits are one type of service provider in many industries, together with governments and for-profit service providers. Nonprofits, as a decentralized system, can better meet diverse and heterogeneous demands from the community (Weisbrod, 1988). Compared with the for-profits, nonprofit organizations have more trust and less information asymmetry problems because of non-distribution constraints (Hansmann, 1980). However, the nonprofit sector has its Achilles' heel, the voluntary failure (Salamon, 1987), encapsulated as "philanthropic insufficiency" – the inability to generate sufficient and reliable resources to scale up services; "philanthropic amateurism" – the inability to hire professionals to provide professionalized services; "philanthropic particularism" – only focus on particular subgroups of the population; and "philanthropic paternalism" – community needs are defined by those who have resources. The first two failures are particularly relevant to compensation and human resource management. Nonprofits have the motivation to solve the insufficiency and amateurism through marketing services and replacing volunteers with professionals (Maier, Meyer, & Steinbereithner, 2016).

Philanthropic insufficiency pushes nonprofits internally to devote more efforts to resource development. Externally, the call for doing more with less and increasing efficiency justifies commercialism: reliance on commercial revenue (James, 1998) and adopting business-like approaches (Maier et al., 2016). Therefore, commercialism has made its way into the nonprofit sector (Eikenberry & Kluver, 2004).

Commercialism embraces profits and efficiency, which might erode values, encourage over-consumption, and bias education, among numerous evils as elaborated by Jacobson and Mazur (1995). The nonprofit sector is co-opted by commercialism, which goes against the essential role of the nonprofit sector as value guardians, service providers, advocates, and builders of social capital (Salamon, 1999). Critical school scholars articulate that marketization approaches are detrimental to democracy and erosive to the value of civil society (Eikenberry & Kluver, 2004). Numerous studies have depicted that commercialism takes hold in the nonprofit sector, and commercial revenue grows dramatically (Child, 2010; Eikenberry & Kluver, 2004; Kerlin & Pollak, 2011; Salamon, 1999, 2015). The argument that commercialism can change organizational behavior is established, but empirical evidence about the impact of commercialism on pay to workers is sparse.

The dissertation examines two broad questions: 1. Does the nonprofit sector pay differently than the for-profit sector? 2. What is the effect of commercialism on the nonprofit pay? It examines the nature of nonprofit wage differential and the consequence of commercialism.

Compensation and pay are complex, as they are jointly determined by factors on the individual, organization, occupation, industry, and state levels (Werner & Gemeinhardt, 1995). Individuals have heterogeneous preferences and motivations. Organizations have different behaviors and decisions about their allocation of resources and profits. Different occupations have different requirements for job skills and human capital. Industries are differentiated by how collective is the nature of the goods or services they provide. Finally, states might be different in policies and regulations.

Mirroring the different levels of the compensation decisions, prevailing theories explain the phenomenon on different levels. To answer the question on the individual level, I draw on social psychology explanation of altruistic motivation, which precedes the donative labor theory in the nonprofit pay study. To answer the industry level question, I adopt compensating wage theory. I develop hypotheses according to the levels of theories.

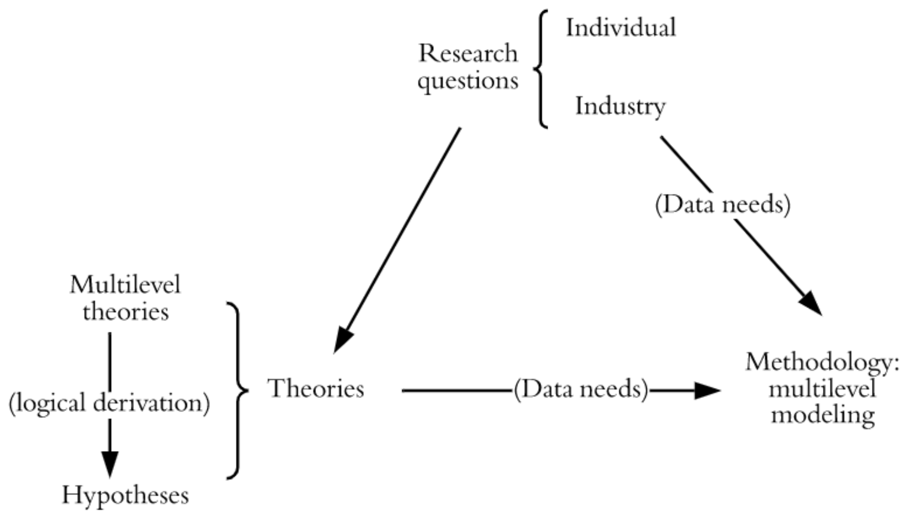


*Figure 1. Research questions and data needs*

The multilevel nature of research questions corresponding to the theoretical frameworks on discrete levels requires data on corresponding levels. Cross-Classified Random Effects Modeling (CCREM) can fulfill the needs because it can decompose variance components on different levels and properly represent the variability and effects from different sources (Kreft, Leeuw, & Aiken, 1995; Raudenbush & Bryk, 2002). In other words, CCREM can estimate unbiased and efficient estimates of fixed coefficients while modeling the variability of interest variables on the macro/contextual level (Kreft et al., 1995; Raudenbush & Bryk, 2002).

I use nationally representative data pooled from Census 2000 and the American Community Survey (ACS) 2005-2016. The data is merged with Statistics of Income from the Internal Revenue Service (IRS). Merging the data with detailed individual-level information to the organizational finance information has closed the gap of compensation studies based solely on either individual data or administrative data.

Level-1 includes 3,017,110 observations with detailed human capital and demographic information as well as sectors. Level-2 includes 38 industries, 303 occupations, and 50 states and DC. Modeling for fixed effects is essentially regression analysis. Random effects of nonprofit pay differential on industry and occupation levels are modeled as a probability distribution of nonprofit pay differential. Before drawing the conclusion, I check the robustness and sensitivity of the estimation. I use different structures on Level-2, including the interaction level of industry and occupation, and adding the state level. Then I use different datasets, including dropping higher education and hospital industries, using Census 2000 only, having different industry categories, and including part-time workers on Level-2.

The results show that nonprofit workers earn 5.7 percent less on average than comparable for-profit workers. This effect is conditional on the industry and occupation effects. In other words, a negative 5.7 percent on Level-1 is the donative labor effects. In industries where nonprofits have pay advantages, the sectoral pay differential will be less negative than -5.7 percent. In industries with pay disadvantage for nonprofits, the sectoral pay differential will be more negative than -5.7 percent. It is a similar situation with occupations. My second research question is to examine the effects of commercialism on pay in the nonprofit sector. Commercialism is measured both as a compositional effect of the for-profit share of workers and as a substantive measure of an inverse of fundraising efforts. Both measures show that commercialism increases pay. Commercialism, an indicator of profit focus and cost minimization, increases the salary as a result of compensating the changed working conditions. Commercialism also increases the gender pay gap, the occupation pay gap, and the sectoral pay gap.

My research provides an economy-wide estimate of nonprofit/for-profit sectoral wage differential that is composed of donative labor effect, industry effect, and occupation effect. I contribute to a consolidated explanation of theories by laying them on corresponding levels with corresponding data. The multilevel modeling of economy-wide data analysis gives equal importance to the random effects of various industries and occupations, which has improved the situation where some industries are studied repeatedly, and others are totally out of radar. Therefore, I also contribute to having established an exhaustive inventory of nonprofit pay differentials across industry and occupation levels. This inventory can serve as a reference and corroboration for future studies.

In chapter 2, I review the literature on nonprofit wage differential under four prevailing theories. In Chapter 3, I deconstruct theories on their corresponding levels and build hypotheses accordingly. Chapter 4 describes detailed data sources, data cleaning processes, analytical tools, and model specifications. Chapter 5 presents the results, and Chapter 6 discusses the findings, contribution and limitations of my research.

# Chapter II. Literature Review

All paid jobs belong to a particular industry and a particular occupation. Employees are nested in a higher-level structure when they are members of units such as organizations, industries, and occupations. The pay for employees not only reflects their work efforts and abilities but also manifests features of the industry and occupation that they work for. Industries are classified in the North American Industry Code System (NAICS), and occupations are classified in the Standard Occupational Classification (SOC). The extensive lists suggest that industries and occupations have boundaries, and there are differences between these categories. Nonprofit and for-profit sectors share most industries and occupations, which imposes an additional complexity to sectoral pay differential studies, because the sectoral pay differential may catch the features of industries and occupations that are varying themselves.

Despite the importance of linkage between pay and structures on the macro level, prevailing studies on the nonprofit wage differential apply a micro view and an individualist approach. They treat industries and occupations as background variables without further scrutiny, with a few exceptions such as Leete (2001) and Krueger and Summers (1988). To lay a foundation for multilevel conceptualization and analysis, I bring together two strands of literature: nonprofit pay studies and nonprofit industries and occupations. In this chapter, I review nonprofit pay differential literature guided by major compensation theories. Then I examine the literature on industry and occupation pertaining to nonprofits, based on which I argue that industries and occupations should be integrated into a holistic analysis of nonprofit pay differential.

## 2.1 Salary and Compensation in the Nonprofit Sector

Major theories on nonprofit compensation include donative labor theory, compensating wage theory, attenuated property rights theory, and efficiency wage theory. Donative labor theory and compensating wage theory predict nonprofits to pay less than for-profit firms, whereas attenuated property rights theory and efficiency wage theory predict nonprofits to pay more than for-profits. In this part, I review what empirical studies on the cross-sectoral pay differential tell us about the major theories.

### Donative labor theory.

Donation and volunteering are an essential part of American life. Around 63 million people volunteered 8.7 billion hours to their communities in 2014, which is equal to 5 million full-time jobs (*America's Nonprofit Sector* - *Revenues*, 2016). In 2015, the total charitable giving amounted to $373.25 billion, and 70 percent came from individuals (*America's Nonprofit Sector* - *Impact*, 2016).

Accepting low pay to work for nonprofit organizations is another form of donation (Lewis, 2010; Preston, 1989; Weisbrod, 1983). Donative labor theory argues that altruistically motivated individuals are willing to accept a low pay in order to have the opportunity to serve the underrepresented (Weisbrod, 1983), or reify their religious or political commitment to social change (Lewis, 2010; Rose-Ackerman, 1996), among other possible values such as liberalism (Lewis, 2010).

Weisbrod (1983) first proposed donative labor theory in a study that found public interest lawyers earned 20 percent less than comparable attorneys working in for-profit firms. Subsequent questions in his research revealed that 45 percent of the lawyers knew beforehand that they would not be better off financially from being public interest lawyers. They did not regret their choices. Furthermore, the public interest lawyers did not expect to use their nonprofit experience as an investment for better-paying jobs in the future, which means their sacrifice is the end instead of the means. Also, these lawyers seem to favor positions that can contribute to social good rather than monetary gain. Weisbrod (1983) finds that 43 percent of public interest lawyers choose to work for schools or governments that usually pay lower than private firms. In short, he argues that altruistic motivation leads to negative wage differential for lawyers in nonprofit organizations.

With the main missions of serving the public good and producing positive social externalities (E. Brown & Slivinski, 2018; Preston, 1989; Rose-Ackerman, 1996), nonprofit organizations provide a better platform than government or for-profits to attract individuals with altruistic motivations to materialize their own values or ideology in a bigger social context (E. Brown & Slivinski, 2018; Cassar & Meier, 2018; Handy & Katz, 1998; Rose-Ackerman, 1996; Weisbrod, 1983). Lewis (2010) finds that the overrepresentation of lesbians and gay men in nonprofit organizations is attributable to their altruistic motivation.

Handy et al. (2007) concur that nonprofit executives choose nonprofit jobs because they identify with the mission of the organizations that reflect their values and beliefs, despite the lower pay than their for-profit counterparts. Ideological nonprofit entrepreneurs prefer managers and workers who share their vision (Rose-Ackerman, 1996). Smart nonprofit managers thus might use a lower salary to filter for employees with altruistic motivation (Handy & Katz, 1998) because altruistically motivated individuals can be more productive with less supervision. For example, nonprofit hospitals use performance-based bonus reward structures less than for-profit hospitals (Roomkin & Weisbrod, 1999) to screen managers who share the organizational goal.

Altruistic workers select jobs based on the meaningfulness of work rather than the monetary incentive (Cassar & Meier, 2018). The meaningfulness of work includes competence, autonomy, and relatedness (Ryan & Deci, 2000). Cassar and Meier (2018) explain that people develop joy and satisfaction from their competence to solve problems or intellectual challenges, which explains why scientists commit their weekends to research and innovation. Arguably, when nonprofit workers can solve some social issues or help disadvantaged groups, the process of being able to help is a source of satisfaction.

Autonomy and relatedness also enrich the meaning of work (Cassar & Meier, 2018). When people have a sense of belongingness or connectedness, they are more likely to work harder and like the job better (Ryan & Deci, 2000). Benz and Frey (2008) find that people working with smaller firms are more satisfied because the structures of small firms are less hierarchical than large organizations. Nonprofit jobs are generally interdependent (Ben-Ner et al., 2011), less hierarchical with more equality, such as narrower pay gap and less discrimination (Ben-Ner et al., 2011; Cassar & Meier, 2018; Faulk, Edwards, Lewis, & McGinnis, 2012). Therefore, nonprofit jobs might be meaningful to altruistic workers.

Considering the dimensions of competence, autonomy, and relatedness (Cassar & Meier, 2018; Ryan & Deci, 2000), the meaning of jobs might have implications on different occupation ranks. Using the 1979 Current Population Survey data, Preston (1989) finds that clerical workers earned comparable wages in two sectors, but managers and professionals earned 5 to 20 percent less in nonprofits than in for-profits after accounting for human capital, industries, occupations, and selected job characteristics. Preston (1989) explains, although nonprofit workers choose to participate in “socially worthwhile organizations” that produce social benefits, nonprofit managers are more closely tied to social benefits provision than the blue-collar workers.

Nonprofit managers have the power and autonomy to decide social programs, which concurs the explanation that autonomy is related to the meaning of work (Cassar & Meier, 2018; Ryan & Deci, 2000). Thus, the willingness to donate labor probably varies by occupation.

Donation is a gift-giving behavior. Donative labor theory indicates that nonprofit workers donate part of their salary or labor to nonprofit organizations (Lewis & Ng, 2013) as gifts. Adloff (2016) distinguishes altruistic giving behavior as different from the giving behavior with self-interests and reciprocal purposes. Altruistic behavior is "motivated mainly out of consideration for another's needs rather than one's own" (Piliavin & Charng, 1990, p. 30), whereas reciprocity happens when “the giving of a gift initiates a cycle of receiving and reciprocating with a counter-gift” (Barman, 2017, p. 274).

If giving, or labor donation, is reciprocal, it can be compensated. Economists in this line argue that nonprofit workers enjoy more satisfaction than comparable workers in the for-profit sector because the lower pay is compensated by satisfaction (Benz, 2005; Handy et al., 2007; Jones, 2015; Leete, 2001; Lewis & Frank, 2002; Mirvis & Hackett, 1983; Preston, 1989). Andreoni (1990) indicates that satisfaction as a type of utility and impure altruism since donors experience “warm-glow.” Any utility has to be compensated, according to the assumption of the economic man who tries to maximize the utility. Evren and Minardi (2017) define warm-glow as “prosocial behavior that causes the actor to experience positive feelings, apart from its social implications” (p.1381). It might be either intrinsically motivated as "pleasure of social acclaim" or extrinsically motivated, such as improving one’s social image or avoiding guilt (Evren & Minardi, 2017).

Scholars from disciplines other than economics have questioned interpreting satisfaction and warm-glow as a compensable utility. Friedland and Alford (1991) argue that the utility is volatile and "socially and historically structured" (p. 234), and thus the maximization is resistant to computation. No one can compensate things incomputable even if s/he intends to. Therefore, warm-glow is not pecuniary (Elster, 2011) nor reciprocal (Barman, 2017), no matter whether it is intrinsically or extrinsically motived. The non-reciprocity distinguishes donative labor theory without anticipation of return from the compensating wage theory with anticipation of return.

**Compensating wage theory.**

Compensating wage theory is about matching the worker's preference with job characteristics (Ehrenberg & Smith, 2018). The essence of the compensating wage theory is that "jobs with disagreeable characteristics will command higher wages" (Smith, 1979, p. 339). Therefore, jobs with higher risks of injuries, lower occupational safety, or less desirable are paid better. However, an empirical test of compensating wage theory encounters obstacles due to heterogeneous tastes of workers and difficulty in specifying *a priori* disagreeable job characteristics. Nonetheless, a common-sense list of job characteristics might include strenuous physical work, repetitive or stressful jobs, fast pace, location, lack of freedom or security, commuting time, and work shifts (Borjas, 2007; Krueger & Summers, 1988; Smith, 1979).

Nonprofit organizations generally offer working conditions with pleasant amenities (Hallock, 2000; Handy et al., 2007; Ruhm & Borkoski, 2003). The known nonprofit work amenities include family-supportive policies, a more egalitarian workplace, flexibility in work schedules, less rigid environment, greater job stability, autonomy, more control over the work performed, building a reputation for a public career, interesting and challenging jobs, not working toward a financial bottom line, and shorter work hours (Ben-Ner et al., 2011; Hallock, 2000; Handy & Katz, 1998; Handy et al., 2007; Leete, 2000; Preston & Sacks, 2010; Ruhm & Borkoski, 2003). If workers care about those agreeable amenities, they should be willing to pay for them by accepting lower pay (Mas & Pallais, 2016). Conversely, they would require a higher wage for jobs without such amenities, or if jobs have conflicts with the strong values and beliefs held by ideological workers (Ben-Ner et al., 2011; Frank, 1996).

Both donative labor theory and compensating wage theory predict a negative outcome of the nonprofit wage differential. However, they are different in several aspects. Donative labor theory is built on altruistic and intrinsic motivation that working itself is a source of satisfaction, whereas compensating wage theory implies exchange and tradeoff between salary and working conditions, which is related to the extrinsic motivation. Therefore, donative labor theory based on altruism is more about individual characteristics, while compensating wage theory is contingent on the external monetary return and related to job characteristics. The distinction between intrinsic and extrinsic orientation leads to potential motivation sorting for jobs.

**Attenuated property rights.**

Economic analyses of property rights assume that top decision-makers have private property rights to the profits or surplus of the firm (Borjas, Frech, & Ginsburg, 1983), and "any reduction in the rights of the top decision-maker leads to attenuated property rights, … [and] the attenuation of property rights leads to higher costs" (p. 4). Attenuated property rights theory is relevant to the nonprofit sector because of the non-distribution constraints. Nonprofit organizations are often exempt from property, sales, and corporate income taxes (Hansmann, 1980, 1987). In return for the tax advantages, nonprofits are subject to the non-distribution constraints. Nonprofits are not allowed to distribute the profits or surplus among board members, managers, or staff, beyond a reasonable salary (Hansmann, 1980). Therefore, nonprofits do not have the incentive to reduce the cost by lowering salaries to workers. What is more, nonprofit managers might derive utility in paying high wages to employees, such as enhanced loyalty and increased working efforts.

Paying a higher salary is possible. Although the nonprofit corporation law prohibits distribution of profits, it is hard for the law to control unnecessarily high wages because the enforcement of non-distribution constraints is "placed exclusively in the hands of the state's attorney general" (Hansmann, 1980, p. 873). Furthermore, the law might apply to top-earning management but not so much to the mid-or-low-rank staff since their salaries are not high enough to touch the ceiling. Therefore, nonprofit managers might choose to pay higher wages to employees (Preston, 1988) as a result of not being able to share the profits of the organization.

Borjas et al. (1983) study the nursing home industry with four types of ownership: for-profit, government, nonprofit-secular, church-related. For-profit organizations have private property rights and are allowed to make and distribute profits. The other three types are not allowed to distribute profits to managers. They find that the pay rate in government is significantly higher than for-profits, but the difference in pay between the nonprofits and for-profits is not significant. The insignificance between for-profits and nonprofits remains true in three larger occupation groups in this industry: licensed practical nurses, registered nurses, aides and orderlies. Their finding of for-profit/government pay differential seems to support the attenuated property rights theory, but the result on for-profit/nonprofit pay differential does not support the theory.

Preston (1988) studies the child-care industry with only nonprofit and for-profit service providers. Part of the industry is unregulated and owner-controlled, where small firms compete to provide services with low fixed costs and free entry. They are mostly for-profit organizations. The other part is regulated and manager-controlled with no ownership. They are mainly large nonprofit organizations seeking federal funds, which impedes entry and competition in the industry. Preston (1988) finds that non-regulation and free competition leads to insignificant sectoral pay difference. By contrast, in the regulated branch, nonprofit workers earn 5 to 10 percent higher than comparable for-profit workers. Preston (1988) argues that less competition and more barriers to entry of new firms lead nonprofit managers to pay higher wages. However, Preston (1988) also mentions that the non-federally regulated is full of small private firms, and the regulated part has many large nonprofits. Studies show that large organizations pay more (Brown & Medoff, 1989; Krueger & Summers, 1988), and this potential relationship between size and pay is not excluded from the study.

*Mediating effects of service quality.*

No incentive to accumulate surplus does not necessarily mean that nonprofit managers will choose to pay higher salaries. They might use the surplus to increase service quality (Holtmann & Idson, 1993; King & Lewis, 2017). Nonprofits are often founded to provide collective goods or trust goods that clients have information disadvantage (Weisbrod, 1988). The non-distribution constraints reduce the incentive to cut corners of services (Hansmann, 1987), which is a competitive advantage for nonprofits (Glaeser & Shleifer, 2001). Glaeser and Shleifer (2001) argue that inferior quality services will bring “non-cash reputational cost” to nonprofits (p. 107). It is to the benefit of nonprofits to provide services of quality because services of better quality could not only retain the service prices and profits in the future but also protect the prestige of donors for the organization.

Nonprofits’ pursuit of better quality services and value for serving the disadvantaged stand in sharp contrast with for-profit practices of cherry-picking and creaming the clients (Frumkin & Andre-Clark, 2000). In nursing home industries, Weisbrod (1988) find that nonprofits have more service workers and fewer administrators than for-profit service providers. Even in ostensibly similar services, nonprofits might provide different clients services with subtle attributes such as "humanness" or "encouragement" (Weisbrod, 1988). Higher service quality could explain higher nonprofit pay (Holtmann & Idson, 1993; King & Lewis, 2017; Preston & Sacks, 2010) because higher-quality services may require staff with higher human capital. However, the difficulty in sufficiently controlling the service quality in an empirical analysis may inflate the estimate of the nonprofit pay differential.

**Efficiency wage hypothesis.**

Efficiency wage theory argues that firms pay above-market rate wages can save costs for firms (Akerlof, 1984; Fields & Wolff, 1995; Krueger & Summers, 1988; Thaler, 1989; Yellen, 1984). The implication of efficiency wage theory on pay is related to the supervision of the production process and employees. When the production is easy to quantify and the product quality is easy to track, competitive wages based on piece-rate are the best way to measure the ability of workers (Borjas, 2007). Competitive wage happens when “firms pay a wage that is just sufficient to attract workers of the quality they desire and no higher” (Krueger & Summers, 1988, p. 259). The more unmeasurable the product quality is, or the more difficult supervision is, the more likely firms will use efficiency wages to increase production and efficiency. If we conceive attenuated property rights as the feasibility of positive nonprofit pay differential, efficiency wage theory offers an explanation of motivation on the firm level.

Four models explicate why it is to the firms’ benefit to pay non-competitive rents (Akerlof, 1984; Fields & Wolff, 1995). The first one is the shirking model. When service quality is hard to monitor, firms may choose to pay above-market rate wages to prevent workers from shirking. Sociological studies find that even the most elaborated division of labor, such as the piecework machine shop, cannot guarantee productivity because supervision is always incomplete (Akerlof, 1984). The second model is the turnover model. Excessive turnover might incur high costs of training, capacity building, recruiting and interrupted production. Efficiency wage on the industry level is associated with long tenure and low turnover rate (Krueger & Summers, 1988). The third model is the selection model. Firms can pay higher wages to attract more capable workers at the expense of profits. Preston (1988) regards recruiting over-qualified personnel as inefficiencies in the nonprofits. The fourth model, the fair wage model, is related to the equity theory from social psychology. Equity theory explains that people perceive a relationship to be fair and equitable if what they get is commensurate with what they contribute (Hatfield, Rapson, & Bensman, 2012). "Overpaid" workers might produce more because they might attempt to increase the quantity of production to match the overpaid part of the salary (Akerlof, 1984). Therefore, efficiency wage can raise worker's effort level, induce loyalty, and minimize turnover, eventually increase productivity and reduce related costs (Akerlof, 1984; Krueger & Summers, 1988).

The efficiency wage theory is also explained on the organization level. Efficiency wage was found to be positively related to the company size and negative related to the turnover rate (Krueger & Summers, 1988). Kruse (1992) concurs that adding human capital and occupations brings negligible change on the coefficient of establishment size in wage estimates, and he further excludes the explanation of the working condition. Numerous studies find that nonprofit executive pay is positively related to organization size measured as total revenue (Grasse, Davis, & Ihrke, 2014; Oster, 1998), total number of employees (Grasse et al., 2014), and total assets (Frumkin & Andre-Clark, 1999; Yan & Sloan, 2016). Larger organizations tend to pay more because larger organizations are more complex with more hierarchies, which makes it harder to supervise the employee. The scale of the economy of large organizations might bring more operational efficiency so that they can afford to pay more (Grasse et al., 2014).

Efficiency wage theory mirrors the shift from scientific management to human relationship management. To increase production, firms may choose to boost workers' morale by paying more rather than controlling them through close supervision. The use of an efficiency wage should not be uncommon because actual production in the real world is more likely to be a social process than a completely rational process. Since nonprofits generally provide services rather than products, and the quality of services is harder to measure than the quality of products, nonprofit workers are likely to benefit from the efficiency wage. Very few studies explore the efficiency wage theory in the nonprofit sector. The only study with peripheral relevance is Ito and Domian (1987) study of the symphony orchestras because they find that guaranteed pay is related to budget size, better team production, and reduced shirking. Other researchers also made similar conjectures that nonprofit managers might derive utility from paying employees higher salaries (Leete, 2001; Preston, 1988) when their finding of nonprofit wage differential is positive.

**Economy-wide.**

Most studies on nonprofit wage differential are based on discrete industries or occupations. Findings vary study by study, which suggests the industry effect or occupation effect on the nonprofit pay differential. In the frequently studied industries, including hospitals, social services, residential care, childcare, and nursing homes, studies find positive nonprofit wage differential (Ben-Ner et al., 2011; Leete, 2001; Preston, 1988; Ruhm & Borkoski, 2003). In other industries such as group homes, housing services, and vocational rehabilitation industries, nonprofits pay less than for-profits (Ben-Ner et al., 2011).

As a contrast to the inconclusive findings based on discrete industry or occupation studies, economy-wide (Hirsch et al., 2018; Leete, 2001; Ruhm & Borkoski, 2003) or multiple-industry (Ben-Ner et al., 2011) studies conclude that the sectoral wage difference is not significant. Leete (2001) finds that nonprofit employees earn almost 1 percent less than comparable for-profit employees. The cross-sector pay differential is so small that the literature examining job switching between the for-profit and nonprofit sectors finds insignificant differential between the two sectors (Hirsch et al., 2018; Ruhm & Borkoski, 2003). The findings lead to the conclusion that it is a result of a competitive labor market (Ruhm & Borkoski, 2003).

In the meantime, scholars are cautious about this general conclusion of pay parity. Ben-Ner and associates (2011) note that nonprofits pay more in nursing homes and childcare centers than for-profits but pay less in group homes. Ruhm and Borkoski (2003) mark a nonprofit premium in five of the eight poorly-paid industries where nonprofit employment is concentrated. Leete (2001) acknowledges the findings from discrete industry and occupation studies and speculates that "the economy-wide finding here could represent an average of differentials that occur with different strengths and magnitudes across different occupations and industries" (p. 156). Her following disaggregated industry analysis reveals that statistically significant differences occur in 34 of the 91 industries in her study. In the 34 industries, 9 of them have a positive nonprofit differential.

Despite acknowledging the significance of industrial level differences (Ben-Ner et al., 2011; Leete, 2000; Oster, 1998), few studies attempted to explicitly model the reason for such variation. Jones (2015) tries to reconcile these inconsistencies in findings based on discrete industry studies by proposing a supply and demand mechanism of the donative labor. He argues that

> as long as there are enough motivated workers to meet their labor demands, nonprofits can minimize costs by offering a low wage (thereby, only attracting motivated applicants). However, if nonprofit labor demand is high relative to for-profit firms, the nonprofit cannot rely on motivated workers alone to fill their demand and must offer wages comparable to that of for-profits in order to attract standard workers. (p. 2)

The supply and demand mechanisms determine that nonprofits will not pay higher than for-profits because nonprofits pay either lower when the supply of motivated worker is above the demand, or just equal as for-profits when the supply is lower than the demand. Then nonprofits compete with for-profits for standard workers. Therefore, it cannot explain why nonprofit-dominant industries such as the childcare industry pay more than for-profits. Furthermore, Jones's (2015) operationalization of the market share based on the industry/locality-specific nonprofit shares of labor assumes that there is no mobility of workers across locality and industries, which goes against the assumption of free labor mobility in the market mechanism.

**Summary**

While studies focusing on discrete industries or occupations make important contributions to our understanding of the nonprofit wage differential, the isolation of industry and occupation makes it impossible to understand the integral context where nonprofit wage differential happens. As Lewis (2010) correctly states, “industry and occupation are the most important predictors of nonprofit employment, followed by location” (p. 20). The economy-wide studies include industries and occupations, but industries and occupations are treated as invariant to the nonprofit wage differential.

Aggregating effects from different sources lead to a sweeping conclusion of cross-sector pay parity, which inappropriately simplifies the nonprofit sector as homogeneous and overlooks that the nonprofit sector is hugely diverse and expansive in industries, that universities are different from daycare centers and homeless shelters, and that some nonprofits are self-help groups while others are public charities. After controlling human capital, unmeasured worker characteristics (through fixed effects models), and a variety of job characteristics such as weekly hours, hazard, work shift, commuting time (which aim to exclude compensating wage explanation), Krueger and Summers (1988) find significant and substantial dispersion of wage across industries. Specifically, they find that industries that pay one occupation higher than other industries also tend to pay other occupations higher than other industries, which consolidates the industry-specific effect on wages. Citing an earlier source, Krueger and Summers (1988) concur that "industry and geographic variables are significant in individual earnings functions... This significance, itself, constitutes a deviation from the norms of a competitive market" (p. 262).

### 2.2 Why industry matters

An industry is “a group of firms producing products that are close substitutes for one another” (Forbes & Kirsch, 2011, p. 591). DiMaggio and Powell (1983) highlight that using industry as the unit of analysis shifts the focus of analysis from competing firms or interacting networks to “the totality of relevant actors” (p. 148). Within the industry, firms share suppliers, resources, consumers, and regulatory agencies, which form the environment constraining all organizations within the industry. Organizations within industry categories are similar with production techniques and technologies. "Similar organizations may provide resources to each other and develop mutual dependencies of long duration" (Child & Aldrich, 1988, p. 15). The feedback from the same pool of clients pushes organizations to imitate the leaders. Organizational actors within the industry adopt mainstream practices for reasons of legitimacy or performance improvement (Meyer & Rowan, 1977). Within-industry similarities suggest between-industry differences. Industries are different in aspects of regulatory requirements, barriers to entry, capital intensity, production technologies, consumers, profitability level, the intensity of competition (Ben-Ner et al., 2011; Preston, 1988).

*Differences between industries dominated by nonprofits and for-profits*. Economy-wide, most industries have both for-profit and nonprofit firms and employers, with varying composition proportion of the two sectors (Hirsch et al., 2018; Ruhm & Borkoski, 2003). Nonprofit organizations tend to provide goods with the collective attribute (Ben-Ner & Hoomissen, 1992) “because of the legal restrictions guiding them, [nonprofits] generally will provide a good whose benefits are more heavily weighted towards social benefits” (Preston, 1989, p. 440). Thus, industries dominated by nonprofits also tend to provide collective goods with positive social externalities, such as public radio and public health (Chang & Tuckman, 1996; Fischer, Wilsker, & Young, 2011). By contrast, industries dominated by the for-profit firms tend to provide goods that are of more private nature, more excludable, and easier to commercialize than products of nonprofit dominated industries.

Evidence below suggests that using sector composition to characterize industries is valid. With no reported information of nonprofits, Preston (1989) had to use industry composition to infer nonprofit status for workers. Leete (2001) checked the reliability of inferred nonprofit status from industry information, and she confirmed that “Preston’s constructed variable for nonprofit status does not perform too differently from the status of nonprofit workers as reported on the PUMS” (p.150).

*Implications of the nature of the goods on revenue sources*. Nonprofits generate revenue from multiple sources. Contrary to the general perception that nonprofits rely on donative revenue, revenue from philanthropy only accounts for 9 percent of total revenue in nonprofits, whereas revenue from government comprises 35 percent, and the remaining 56 percent is from fees and charges (Salamon, 2015). The revenue streams are related to the nature of services nonprofits provide (Fischer et al., 2011; Wilsker & Young, 2010; Young, 2017). Organizations providing "private" services, where the benefits accrue to identifiable individuals, such as nursing homes, are more likely to earn income from fees and service charges (Fischer et al., 2011). Nonprofits providing "public" services, such as public health, are more likely to rely on donations. Based on the composition of revenue sources, nonprofits have a different degree of publicness on the spectrum of the collectiveness index (Fischer et al., 2011; Weisbrod, 1988; Young, 2017).

*Implications of revenue sources on nonprofit salary*. Nonprofit organizations are dependent on resource suppliers for survival. The degree of dependence is determined by the importance and concentration of the resource streams (Froelich, 1999; Pfeffer & Salancik, 1978). Organizations relying on donative funding are susceptible to donor and social expectations (Carman, 2011). Donors expect their donations to be used for augmented social benefits rather than high salaries for employees (Carman, 2011). Nonprofits relying on contributions and donations are more likely to report a lower ratio of management (including salary) expenses to the total expense (Cordes & Weisbrod, 1998).

In contrast to donative nonprofits, nonprofits relying on commercial revenue earn income from individual clients or consumers based on provided services, which shifts the locus of control from several major donors to very diffused individuals (Froelich, 1999; Frumkin & Keating, 2010). Furthermore, these nonprofits may have more abilities and opportunities to generate revenue from different sources. Thus, commercialized nonprofits have greater autonomy and flexibility to decide the use and allocation of their revenues. Guo (2006) reports that nonprofit managers with more commercial revenue have the ability to increase pay to attract and retain qualified staff.

**Industries and Commercialism in Nonprofits.**

Nonprofits commercialize if they decide to “produce goods or services with the explicit intent of earning a profit” (Tuckman, 1998, p. 26). Underlying reasons are multifold (Cortis, 2017; Guo, 2006; James, 1998; Salamon, 2015). One reason is the “financial squeeze,” where governments cut funding for nonprofits as a response to the conservative ideology to boost the volunteerism of nonprofits (Salamon, 1993, 1999, 2015). The second reason is that the government transferred funding mechanisms from producer subsidies to consumer subsidies, such as tax expenditures and vouchers, so that clients can choose between for-profit or nonprofit service providers (Salamon, 2015). As a result, nonprofit service providers have to engage in market behaviors in order to compete for clients. The third reason is that with more involvement of the for-profit sector in government contracts, nonprofits need to compete with for-profits and learn how to market their services (Salamon, 2015). The above reasons indicate that nonprofits commercialize to respond to the changing environment and reduced donative revenue, to cross-subsidize their services, and to enhance financial sustainability. Additionally, studies on universities suggest that organizations might also commercialize to exploit the funding opportunities rather than responding to the scarcity of resources (Powell & Owen-Smith, 1998), or a result of a long-time effect of external pressure and environmental influence (Foster & Bradach, 2005; Kerlin & Pollak, 2011).

James (1998) defines commercialism as "the degree of reliance on sales revenue rather than donations or government grants" (p. 27). Based on the definition, industries dominated by for-profits are more commercialized than industries dominated by nonprofits from the perspective of sources of revenue. Surprisingly, *A Dictionary of Nonprofit Terms & Concepts* published in 2006 does not include commercialism. Instead, it introduces commercialization as a process for generating commercial revenue and as a process of competition between for-profits and nonprofits (Smith, Stebbins, & Dover, 2006).

As a comparison, other dictionary definitions of commercialism emphasize the attitude and intent toward profit-making. Commercialism is defined neutrally as "commercial spirit, institutions, or methods" by the Merriam-Webster dictionary, or it is “an attitude or philosophy devoted to supplying goods and services and make profits.”[1] Collins dictionary defines it with a pejorative sense as "the practice of making a lot of money from things without caring about the quality." Cambridge dictionary defines it as "principles and activities of commerce, especially those connected with profit rather than quality or doing good."

These definitions echo Grønbjerg (2001)’s lament that the overreliance on effectiveness and efficiency forces nonprofits “to downplay their traditional pride in quality of services (the argument for why they should be preferred service providers) and good faith efforts (the explanation for what they were paid) in favor of market-like behavior” (p. 293). The differences in the definitions between the intent and the revenue have implications on the operationalization of the concept of commercialism. An organization has to have an intention to commercialize before it starts the process of commercialization to generate commercial revenue. In this sense, the intent to commercialize should be the antecedent of the commercial revenue.

The way for nonprofits to commercialize is to adopt a commercialism ideology and for-profit business management strategies (Tuckman, 1998) through embracing efficiency and cost-

[1] https://www.vocabulary.com/dictionary/commercialism

benefits mentality (Froelich, 1999). The intent and strategy of commercialism bring fundamental changes to nonprofit organizations' operations and practices. Powell and Owen-Smith (1998) explain that universities engaging in commercialized Research & Development made institutional arrangements to facilitate external linkages and internal administration. The increased hierarchy and bureaucracy of nonprofit organizations as a result of commercialism go against the "soul" of America's nonprofit sector (Salamon, 2015, p. 1) by compromising the democracy and equity values traditional nonprofits embrace.

The resultant changes from commercialism also manifest in human resource practices. Commercialized nonprofits are more instrumental and purposive and have stronger convictions for managerialism and professionalism (Hwang & Powell, 2009; Maier et al., 2016). Hwang and Powell (2009) note a decline in professionals in substantive fields (such as lawyers and doctors) and an increase in management professionals with administrative expertise as nonprofit organizations get more rationalized or commercialized. Other researchers concur that arts organizations favor professional managers over technical experts even though those managers know little about art forms, an example cited by Froelich (1999).

Unlike professionals in substantive disciplinary areas such as lawyers, social workers, or medical doctors who align themselves with normative orthodoxy and who are less affected by environmental pressures, managerial professionals are more vigilant to environmental changes. DiMaggio and Powell (1983) have discussed the crucial role of managerial professionals in disseminating the norms and standards that eventually lead to isomorphic structures and practices of organizations. They use their widely applicable organizational intelligence to rationalize the organization through socialization and diffusion (Hwang & Powell, 2009). The more managerial professionals diffuse the management practice and industry standards through their mobility among different organizations (Hwang & Powell, 2009), the more likely an isomorphic result occurs: organizations within the same industry are similar in practices and organization structures (DiMaggio & Powell, 1983).

Accompanying the managerialism in commercialized nonprofits is professionalization through replacing volunteers with full-time staff (Maier et al., 2016). Over-professionalization is detrimental to the nonprofit sector because it implies "alienating people from the helping relationships they could establish with their neighbors and kin … by redefining basic human needs as 'problems' that only professionals can resolve" (Salamon, 1999, p. 13).

**2.3 Why occupation matters**

As a classifier for jobs, occupations reflect ability and skill attainment, earning levels, and socioeconomic status. The distinction of occupations makes it an interesting area in pay studies, such as lawyers (Weisbrod, 1983), registered nurses (King & Lewis, 2017), or occupation pay comparison studies (Lewis, 2018). Occupations have different structures and conditions, including hazards, union status, and environmental amenities (Macpherson & Hirsch, 1995). Nonprofit jobs spread across most occupations but ten of them, including clergy, social service managers, health technicians, and educators, account for the majority of the nonprofit employment (Addison, Ozturk, & Wang, 2018; Hirsch et al., 2018; Ruhm & Borkoski, 2003).

Scholars examined the cross-sector wage differential caused by occupations. Production, maintenance, and material moving workers tend to concentrate on for-profit organizations (Bishow & Monaco, 2016). In contrast, nonprofits employ more managers, professionals, service workers, and female workers (Bishow & Monaco, 2016). Controlling for these occupational characteristics in the nonprofit sector, studies reveal less dispersion in cross-sectoral pay differential (Leete, 2000; Preston, 1990b). Particularly, nonprofit wage structure has more gender pay parity, lower racial discrimination, lower gay-straight pay differences, and more wage equity between ranks than for-profit firms (Faulk et al., 2012; Hallock, 2002; Hirsch et al., 2018; Leete, 2000, 2006; Lewis, 2010; Preston, 1989; Ruhm & Borkoski, 2003).

Nonetheless, women earn less than men in both the nonprofit and for-profit sectors (Lanfranchi & Narcy, 2015; Leete, 2001; Macpherson & Hirsch, 1995; Preston, 1990). The gender pay gap gets wider with persistent "Glass Ceiling" that Gibelman (2000) defines as "transparent but real barriers, based on discriminatory attitudes or organizational bias, that impede or prevent qualified individuals, including (but not limited to) women, racial and ethnic minorities, and disabled persons, from advancing into management positions" (p. 251).

Glass ceiling hides the discriminatory nature of pay because, for instance, the gender pay gap may appear to be caused by the difference in positions. Sampson and Moore (2008) document a persistent male pay advantage due to the "glass ceiling": senior management positions are predominantly owned by men, "women account for 47 percent of U.S. workforce and less than 8 percent of its top managers." Even in similar senior management positions, female managers earned 72 percent of male managers' salaries in 2005. Furthermore, the gender pay gap is larger for older workers than for younger employees (Sampson & Moore, 2008).

The nonprofit sector experiences the same situation. In the study of fundraising professionals in Northeast, Sampson and Moore (2008) find that women dominate a large number of low-paying jobs, women earn less in the same position, fewer women get pension plans than men, women tend to work for smaller organizations who generally pay less than larger organizations, more women take their time off from the career than men mainly for reasons of childcare, and women are less likely to be promoted to senior managers.

**Female Overrepresentation.**

One aspect of occupational effect on wage is the female dominance in the nonprofit sector (Boris & Steuerle, 2017; Faulk et al., 2012; Hirsch et al., 2018; Lanfranchi & Narcy, 2015; Leete, 2006; Mirvis & Hackett, 1983; Onyx & Maclean, 1996). Men and women differ in their preference for working conditions. Preston (1990b) find that nonprofit wage structure largely explains the female dominance in the nonprofit sector. Mas and Pallais (2016) find that women, especially those with young children, are more likely to choose jobs with flexible schedules than men. The nonprofit occupation structure and job characteristics are featured with family-friendly practices, flexible work schedules, and sick leave, all of which are especially attractive to women who have more family duties (Handy et al., 2007; Mirvis & Hackett, 1983; Preston, 1990b).

Therefore, employees might sort themselves in nonprofit jobs due to altruistic motivation or occupation structure in the nonprofits, as discussed previously. Alternatively, they might sort to nonprofits due to other reasons such as the ability. Several studies acknowledge that the inability to exclude ability sorting is one of their study limitations (Jones, 2015; Leete, 2001; Preston, 1989). Macpherson and Hirsch (1995) address this issue by explaining the composition effect where historical gender discrimination against women leads women to crowd into low-paying occupations. Over time, the female proportion evolves into an ability indicator, as women with more ability to move out and men with less ability to move into lower-paying occupations. Macpherson and Hirsch (1995) argue that the female proportion on the occupation level stands for job preference and tastes for women, but it is an indicator of the ability of men. The study concludes that models without controlling female proportion might lead to biased estimates on wage differential (Macpherson & Hirsch, 1995).

## Summary

Discrete industry and occupation studies produce negative, non-significant, and positive nonprofit wage differentials. Scholars of economy-wide studies are cautious about drawing a definitive conclusion by acknowledging the significant inter-industry difference in the nonprofit pay differential. Leete (2001) speculates that there might be several different forces leading to sectoral wage differential in addition to donative labor theory. Two major problems cause conflicts among findings. The first problem is mixing the explanatory level of theories, and the second is confounding the industry and occupation effects in the estimates.

Theories on different levels have their boundaries and explain different mechanisms: there is no grand theory explaining whether nonprofits pay higher or lower as an aggregate of individual, industry, and occupation effects. Donative labor theory built on altruism explains individual behavior and preference. Attenuated property rights theory expounds on the behavioral differences between organizations that have property rights and limited property rights. Lastly, efficiency wage theory, a much less studied one in the nonprofit sector, predicts that the above-market-rate wage is helpful to save costs for organizations.

Based on their inter-industry study results, Krueger and Summers (1988) conclude that “the sources of wage differentials need to be isolated” (p. 281). More importantly, these theories predict different results. Without articulating the level of analysis, we cannot anticipate the sign of the estimate of the cross-sectoral wage differential. Without disentangling effects from different levels, we are not clear whether the estimates stand for individual nonprofit workers, nonprofit organizations, or industries dominated by nonprofits.

The second problem concerns how to appropriately control and model the effects of industries and occupations. Krueger and Summers (1988) argue that the combination of industries and occupations is more important than other structural characteristics, such as location and union status. Warren (2008) highlights the relationship between industries and occupations: “an establishment's industry is a major determinant of its occupational composition, comparing for-profit and not-for-profit establishments within the same industry provide the best means of examining the effects of profit status on occupational staffing patterns” (p. 16). Kim and Charbonneau (2018) argue that cross-sector wage differentials “should be made for similar workers and jobs between the sectors” (p. 5). When controlling for more than 40,000 interactions between industries and occupations, Leete (2001) finds occupations and industries explain significant variation in pay. She explains that instead of the difference between nonprofit and for-profit sectors per se, the wage differential reflects “the public good content of the product produced” (p. 163).

If industry and occupation play such an important role in cross-sector wage differentials, they should not just be controlled. Instead, industry and occupation should take a more active role as the context for cross-sectoral wage differential analysis. Although individual behavior offers observable convenience, individual actions are not independent of the social context (Friedland & Alford, 1991).

Beyond the need to actively model the wage dispersion on industry and occupation levels, it is necessary to explain the dispersion. To summarize, it is compelling to consider multiple levels so that we can reinstitute the explanatory power of theories on different levels, and the resultant clarity can depict the real nature of the nonprofit pay differential.

# Chapter III. Integrated Theories and Hypotheses

As reviewed in the previous chapter, empirical evidence on whether nonprofit workers donate their labor to the organizations shows that nonprofit wage differentials differ by industries and occupations. Theories explain nonprofit wage differentials from different levels. Donative labor theory illustrates that altruistically motivated individuals tend to select to work for nonprofit organizations for lower pay (Handy & Katz, 1998; Weisbrod, 1983). Compensating wage theory predicts the effect of pleasant working conditions on pay between organizations or industries(Borjas, 2007; Smith, 1979). Efficiency wage theory explains that firms producing goods with less measurable qualities or organizations with larger sizes tend to pay more than needed to boost work morale and increase productivity (Akerlof, 1984; Krueger & Summers, 1988). Lastly, attenuated property rights theory on the sector level differentiates the ownership of the organizations and their consequences. Accordingly, I develop research hypotheses based on different levels and then incorporate moderating effects across the individual level and industry level. Due to the lack of organizational-level data, I will not develop any hypothesis related to attenuated property rights theory. Therefore, I have three units of analysis: individual, industry, and occupation.

Altruism is part of human nature, with some people being more altruistic than others (Piliavin & Charng, 1990). Altruists feel that they have a moral obligation or commitment to contributing to charitable services (Rose-Ackerman, 1996). Thus, they are more likely to engage in philanthropic behaviors, such as donating their labor as volunteers or donating money to the causes they support. Producing positive social benefits and increasing social welfare make altruistic individuals feel happy and satisfied (Handy et al., 2007; Preston, 1989; Weisbrod, 1983). Cassar and Meier (2018) find that altruistic workers prefer meaningful jobs to monetary rewards. Nonprofit organizations provide a space for altruistically motivated workers to contribute their efforts (E. Brown & Slivinski, 2018), because nonprofit missions, such as promoting equality and democracy, building social capital, or engaging in associations and advocacy, are more meaningful than for-profit jobs with the sole goal to maximize profits.

Furthermore, nonprofit jobs seldom involve manufacturing that is characterized as repetitive work, fixed schedule, and rigid environment. Nonprofit jobs tend to be more service-oriented and require frequent interactions with clients and customers, which is often refreshing and challenging. When nonprofit workers are able to help clients to solve their problems, the positive reinforcement of accomplishment can enhance their sense of competence.

Furthermore, nonprofits are often founded by ideological entrepreneurs who have strong beliefs about how and to whom services should be provided (Rose-Ackerman, 1986). Scholars theorize that nonprofit managers might utilize the lower pay as a screening device to filter for intrinsically motivated workers because intrinsic motivation can guarantee nonprofit product quality, which is especially important in social, medical, and educational services (Handy & Katz, 1998; Hansmann, 1980). Managers' screening for workers with intrinsic motivation can bring multiple benefits to the organization. Nonprofits can pay low salaries to them, and they still have a high commitment to jobs. Self-selection of employees and selection of managers thus formulate a bi-directional selection, which makes employment in nonprofit organizations a valid proxy for altruistic motivation. Based on donative labor hypothesis,

**Hypothesis 1**. Although circumstances of industries and occupations might be different, on average, nonprofit workers earn less than comparable for-profit workers.

Job amenities and working conditions are important determinants of acceptable pay for workers, as argued by compensating wage theory. In the dissertation, I conceptualize differences in working conditions to be associated with commercialism on the industry level.

Commercialism, either defined as reliance on commercial revenue or as an attitude toward profit-making, implies changes in behaviors of organizations toward rationalization, efficiency, and cost reduction (Hwang & Powell, 2009; Maier et al., 2016). More commercialized organizations, or organizations in more commercialized industries, are more rationalized. They tend to have forward-looking strategic plans, financial audit systems, and quantitative performance measures (Hwang & Powell, 2009), probably clear profit-making goals as well. These differences can cascade to human resource management practices. Efficiency focus and cost-benefit mindset of commercialism (Froelich, 1999) might make the working environments and conditions less desirable, such as reducing family-friendly practices and the flexibility of work schedules. If workers are willing to pay for good working amenities, the less pleasant working conditions associated with commercialism will lead to their requests for higher compensation.  Lastly, more commercialized organizations are more likely to design the reward system based on extrinsic motivations (Ben-Ner et al., 2011), which might attract extrinsically motivated workers. As a contrast, intrinsically motivated workers who appreciate associative and expressive functions (Frumkin, 2002) tend to sort themselves into traditional nonprofits (Handy & Katz, 1998; Leete, 2000; Mirvis & Hackett, 1983; Steinberg, 1990). Even if altruistically motivated workers choose to work for commercialized nonprofits, they might require higher pay for doing things they do not like (Ben-Ner et al., 2011; Frank, 1996). Therefore, changed working conditions results in the effect of commercialism on pay.

**Hypothesis 2**. Commercialism will increase salary.

Commercialism is not a dichotomous metric. It is a continuum where organizations align with different levels of commercialism. Nonprofits are founded to either respond to government failure (Weisbrod, 1988) or to materialize ideological entrepreneurs' vision for social and political changes (Rose-Ackerman, 1996). In the case of government failure, nonprofits provide collective or redistributive goods that bear "public-good-intensive" (Leete, 2001, p.159), and they have a large portion of donative revenue. Other nonprofits producing private services have greater potential to commercialize and generate more commercial income than nonprofits providing public goods. Accordingly, they have more opportunities to charge for services.

In the case of achieving social and political changes, Rose-Ackerman (1986, 1996) argues that ideological entrepreneurs believe certain ways are better for the clients than others. Due to the particular way they insist on delivering the service or on maintaining the service quality, they might not be willing or able to meet the demand from all clients. They have to select more worthy clients and put others on the waiting list rather than using price rationing (Rose-Ackerman, 1986, 1996; Weisbrod, 1988).

Consequentially, nonprofit persistence of specific quality or a specific type of services (maybe at a higher price) and the unserved clients creates a market niche for for-profits to fill. For-profit firms in the same industry might provide differentiated services (possibly at a lower price and quality) to cater to the needs of the rest of the market (Rose-Ackerman, 1986). Or, for-profits might charge more for a similar service for those who can afford it. Either practice will give for-profit organizations or industries dominated by for-profits to accumulate more financial slack to pay high salaries at their own discretion. In a study of nonprofit executive pay, Frumkin and Keating (2010) find that commercial revenue or earned income from individuals are less subject to monitoring because individual donors are dispersed. It is a different scenario if the funding is from large donors like the United Way. The administrative cost needs to be justified, and fund-using is subject to close monitoring and financial reporting (Frumkin & Keating, 2010).

In short, nonprofits in less commercialized industries should differ from nonprofits in more commercialized industries in aspects of their potential to generate and autonomy to distribute the surplus. Therefore, commercialism should moderate the sector effect on pay.

**Hypothesis 3**. Commercialism raises pay, but it increases pay slower in nonprofits than for-profits.

Managers and non-managerial staff are different in their cross-sectoral pay differential due to their proximity in producing positive social externalities (Preston, 1989). This difference will be further moderated by the commercialism on the industry level due to the sectoral composition of both sectors. Ideological managers sort themselves into nonprofits founded to achieve social or political commitment. Hansmann (1980) and Handy and Katz (1998) argue that the cunning nonprofit board of trustees can design and offer a compensation package that facilitates self-selection (Kreps, 1997) of nonprofit managers to attract intrinsically motivated and truly committed managers. Therefore, they are more likely to concentrate on industries dominated by nonprofits with less commercialism.

In contrast, managerial professionals who care about extrinsic rewards will be more likely to work for-profit firms or commercialized nonprofits (Rose-Ackerman, 1996; Weisbrod, 1988). Commercialized nonprofits prefer professional managers who are trained with business-oriented skills and are good at strategic planning, identifying market niches, and designing measurable targets (Rose-Ackerman, 1996; Salamon, 2015). Managerial sorting, in turn, shape and consolidate organization objectives and missions (Hwang & Powell, 2009) and make the nonprofits they lead more entrepreneurial or more ideological. Managers have a narrower cross-sector pay gap than clerical workers. For clerical workers, studies explain that their narrower sectoral pay gap is because they are far from the realization of organizational goals and missions (Preston, 1989; Roomkin & Weisbrod, 1999), and they share fewer responsibilities than the managers. If this is true, then the difference in commercialism industries should have less impact on clerical workers than managers. In sum, the motivation sorting of managers is likely to create a larger pay gap between managers and non-manager staff in more commercialized nonprofits than traditional nonprofits.

**Hypothesis 4**. Commercialism will increase the pay of managers more than non-managerial staff.

The gender pay gap is narrower in nonprofits than in the for-profits, everything else equal (Addison et al., 2018; Faulk et al., 2012; Lewis, 2018; Preston, 1990b). Due to the different levels of commercialism in each industry, the sectoral effect on the gender pay gap will be moderated by the commercialism.

Gender pay equity is positively related to the female proportion by occupation. In occupations with more females, the pay gap narrows down because men endure more wage penalty, not because females gain in earnings (Addison et al., 2018; de Ruijter & Huffman, 2003; Faulk et al., 2012; Macpherson & Hirsch, 1995). Macpherson and Hirsch (1995) argue that occupation selection is a matter of preference for women. Handy and associates (2007) concur that job characteristics are good predictors for women’s job selection with nonprofits.

The gender pay gap is narrower in the nonprofit sector than the for-profit sector (Leete, 2000; Preston, 1990b; Ruhm & Borkoski, 2003). One reason is the female overrepresentation in the nonprofit sector because featured services and occupations in the nonprofit are more suitable for women (Handy et al., 2007; Preston, 1990b). Another reason is related to the nonprofit values of "humanitarianism, charity, human rights, human well-being," which make them more likely to adhere to affirmative actions for employment and wage-setting (Gibelman, 2000, p. 254).

As commercialism increases the efficiency focus and profit maximization, working conditions will become less pleasant. Changed working conditions might change job decisions for women who care about the amenities. More females might choose less commercialized organizations and industries that offer desirable conditions than males because women need to fulfill more social and familial responsibilities. Gender sorting thus leads to a compositional effect. Faulk et al. (2012) find that in industries dominated by nonprofits, the gender pay gap is narrower.

In more commercialized organizations and industries, changed working conditions will trigger workers to require higher pay, as argued in the compensating wage theory. The external incentives and reward system in commercialized nonprofits will attract more males, whereas women are less responsive to monetary motivation than men (Handy et al., 2007). Therefore, gender concentration based on the sectoral difference depends on the industry where the nonprofit is located. Then, the compositional effect on pay resulting from commercialism will also follow.

**Hypothesis 5**. Commercialism increases the pay for men more than women.

In this chapter, I have developed hypotheses based on donative labor theory and commercialism effect. Altruistic motivation and labor donation are fundamental in the nonprofit sector. I argue that controlling for industry and occupation effects, nonprofit workers earn less than for-profit workers. Compensating wage theory hinges on the working conditions. Literature suggests that commercialism causes changes in the behavior of organizations. Therefore, commercialism will increase pay and will moderate the manger-staff pay gap and the gender pay gap.

# Chapter IV. Methodology

The dissertation examines how contextual factors affect the pay gap between nonprofit workers and for-profit workers. With three units of analysis: individual, industry, and occupation, I apply multilevel modeling to estimate the effect of individual nonprofit status on the pay as well as this effect's variability on industry and occupation levels while controlling for the state level and other variables. In this chapter, I first articulate the choice of cross-classified random effects modeling (CCREM) based on the data structure and unique features of CCREM. Then I describe the variables and data cleaning process. Lastly, I specify models for hypothesis testing.

## 4.1 Cross-classified random effects modeling (CCREM)

Workers are affiliated to, or nest in, certain industries and occupations. Thus, observations under the same industry or the same occupation are not independent due to the same contexts they share. With a different context of industry or occupation, comparable workers experience different effects. For example, the industry effects are similar for hospital workers but different for hospital and daycare center workers, even if workers have the same work experience, race, and educational attainment. In a study of five human service industries where "all types of organizations produce the same service, recruit employees with similar job titles, compete in the same labor markets, and face similar regulations," Ben-Ner and associates (2011, p. 609) find that nonprofit wage differential varies across industries. Similarly, considering how occupations differ in human capital, such as education and vocational skills, occupation categories impose within-group homogeneous effects and between-group heterogeneous effects on workers.

Given the presence of clustering effects from industry and occupation levels[2], ignoring them is problematic because it violates the assumption of independence of observations in the ordinary least squares (OLS) regression models (Bliese & Hanges, 2004; Hox, 2010; Woltman, Feldstain, Mackay, & Rocchi, 2012). Clustering effects imply heteroscedasticity or non-constant errors that are composed of errors associated with the individual level, errors associated with the industry level, errors associated with the occupation level, and errors associated with the state level. Models that do not deal with the non-independent error suffer from aggregation bias, misestimated standard errors, and heterogeneity of regression[3] (Raudenbush & Bryk, 2002).

Scholars paying attention to the effects of the industry and the occupation apply different statistical approaches to these categories. Some choose one category to study (King & Lewis, 2017; Preston, 1988; Weisbrod, 1983). Others control industry and occupation effects or interaction terms between the two categories (Faulk et al., 2012; Leete, 2001). Still others model the dispersion of inter-industry wage and how the pay on industry level differs from each other. Scholars constantly find, and mostly agree, that dispersion of industry wage is stable over a long period (Allen, 1995; Fields & Wolff, 1995; Haisken-Denew & Schmidt, 1991; Krueger & Summers, 1988). The following table summarizes the major approaches used to deal with industry effects.

| | Research Question | Methods | Comments |
|---|---|---|---|

[2] In the multilevel analysis, a level is "a design factor with random effects" (Snijders, 2005).
[3] "Heterogeneity of regression occurs when the relationships between individual characteristics and outcomes vary across organizations… Hierarchical linear models enable the investigator to estimate a separate set of regression coefficients for each organizational unit, and then to model variation among the organizations in their sets of coefficients as multivariate outcomes to be explained by organizational factors" (Raudenbush & Bryk, 2002, p.100).

| | | | |
|---|---|---|---|
| Krueger and Summers (1988) | Wage dispersion on the industry level explained by efficiency wage theory | Step 1: control all possible variables and analyze the effect of industry dummy variables on wage;<br>Step 2: normalize the estimated industry wage differentials as deviations from the (weighted) mean differential. | Not considering sample size and number of categories leads to overestimating of standard deviation (Haisken-Denew & Schmidt, 1991) |
| Leete (2001) | Nonprofit pay differential | 1. 10,432 occupation/ industry cells in which both sectors are represented – as a control variable in OLS;<br><br>2. disaggregated analysis of 91 three-digit industries. | Clustered error presence increases Type I Error (de Ruijter & Huffman, 2003; Raudenbush & Bryk, 2002). |
| Faulk et al. (2012) | The gender pay gap in the nonprofit sector | HLM, 250 industries and 845 occupations generating 16,538 cells | Clustered errors are decomposed;<br>Level-2 cells are mixed with industries and occupations. |

The three methods have different purposes. Krueger and Summers (1988) seek to analyze the inter-industry wage dispersion. They include industry dummies in the regression model and then normalize the wage differentials as the deviation from the mean. Haisken-Denew and Schmidt (1991) comment that including sample size and the number of categories of industries can improve the models. Leete (2001) aims to model the nonprofit wage differential while controlling industry and occupation variables. Her first analysis controlled for interactions of industry and occupation variables, and the second analysis analyzed disaggregated industries. Disaggregate analysis is no different from discrete industry or occupation studies. Controlling interaction terms does not solve the problem of heterogeneous error terms that lead to inconsistent outcomes. As a result, the study shows that significant positive or negative wage differentials in discrete industries sum up to an insignificant overall wage differential (Leete, 2001). Neglecting industry effects can lead us to draw a wrong conclusion that nonprofit workers earn the same wages as for-profit workers even though there is a difference in pay between nonprofit and for-profit workers.

Faulk and associates (2012) put the interaction of industry and occupation on Level-2 as a classification factor. The statistical treatment of industry and occupation decomposes the errors that associate with the industry-occupation cells and improves the consistency of fixed coefficients. However, cells combined of industries and occupations as a unit on Level-2 makes it impossible to separate industry effects from occupation effects.

Hierarchical linear modeling is designed to decompose error terms associated to different structural-level units in clustered data, and to model random effects of Level-1variables across Level-2 units, with an ultimate goal to produce consistent estimates while taking non-independent observations and random effects into consideration (Kreft & Leeuw, 1998; Raudenbush & Bryk, 2002; Woltman et al., 2012). The phenomenon that individual outcomes vary across groups is not just a methodological nuisance that we need to fix (Raudenbush & Bryk, 2002) because "the heterogeneity is not a technical problem but a symptom of something deeper" (Deaton, 2010, p. 451). Therefore, beyond a methodological fix, multilevel modeling also means a shift in the conceptual view on social problems in research.

In my dissertation, groups on Level-2 include industry, occupation, and state. Individuals nest in industries and occupations, but industries and occupations do not nest in each other. Any industry includes many different occupations, and many occupations expand across different industries. The data structure is thus not hierarchical. Instead, industry and occupation cross-classify each other (Figure 2).

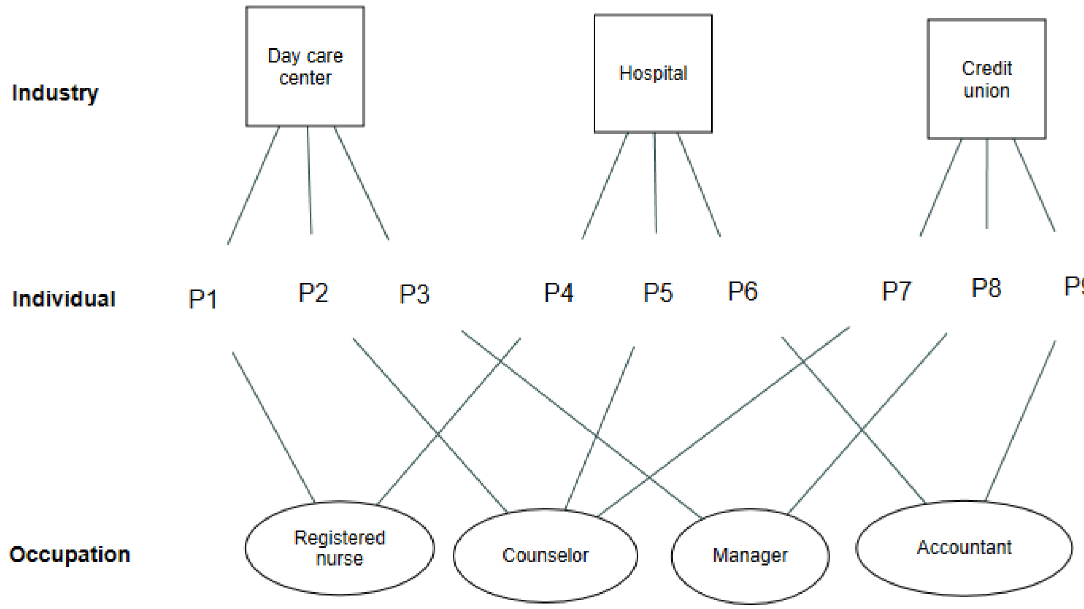


*Figure 2. Network graph*

The dissertation uses cross-classified random effects modeling (CCREM) (Beretvas, 2008a; Hox, 2010; Raudenbush & Bryk, 2002) because CCREM can achieve the following analysis goals. First, it improves the estimation through properly decomposing variance components[4] after taking into account observable characteristics of individuals, industries, occupations, and states. It can specify and model random effects to estimate the unobserved influences attributable to industries and occupations. Specifically, the random coefficient[5] model can assess the extent to which the association between nonprofit status and annual wage varies

[4] Variance components refer to the variances and covariances of the residual errors (Hox & Maas, 2005). They can be decomposed into variance within and between groups (Diez Roux, 2002).
[5] Random coefficients are allowed to vary randomly around the overall mean across higher level units, that is, are assumed to be realizations of values from a probability distribution (Diez Roux, 2002).

across industries and occupations. Thus, it can estimate the unique effects associated with particular industries or occupations after adjusting for explanatory variables.

This dissertation examines how commercialism affects the cross-sector pay differential. In terms of nonprofit pay differential, CCREM outputs include the fixed part containing group-invariant regression coefficients and the random part containing the group-variant residual error terms (Hox & Maas, 2005). The fixed effect of nonprofit wage differential is the partially[6] pooled nonprofit pay differential in the sample, and random effects are differences of the nonprofit wage differential across industries and occupations (Bell & Jones, 2015; Snijders, 2005). CCREM estimates the consistent nonprofit wage differential by taking into account Level-2 random effects. Based on prevailing nonprofit pay empirical studies, random effects modeling is an important component in the dissertation because it can reflect the social reality that nonprofit pay differential varies across industries and occupations.

The effect of commercialism on pay implicates the analysis of the contextual effects[7] of industries. The contextual analysis allows the "simultaneous examination of how individual-level and group-level variables are related to individual-level outcomes" (Diez Roux, 2002, p. 588). To achieve this, there is a need to control for effects of occupations as another Level-2 classification factor and the standard list of variables on human capital and demographic information.

In addition to levels of industry and occupation, compensation varies by state (Biggs & Richwine, 2014). King and Lewis (2017) find that public hospitals are more likely than nonprofit hospitals to concentrate in high-paying states. Furthermore, state-level legislation may affect

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[6] Standard "pooled" linear regression models assume that residuals are independently and identically distributed (Bell & Jones, 2015).
[7] Compositional or contextual effects occur when the aggregate of a person-level characteristic is related to the outcome even after controlling for the effect of individual characteristic (Raudenbush & Bryk, 2002, P. 139-141).

industrial-level factors, such as barriers to entry and competition (Preston, 1988), and states vary in their economic development, which has effects on employee wages. Although there are no state-level predictors in this dissertation, omitting states in the model might lead to bias in the estimation (Leroux, 2019; Moerbeek, 2004; Tranmer & Steel, 2001; Van Den Noortgate, Opdenakker, & Onghena, 2005) of the nonprofit wage differential. Therefore, I put the state as a third cross-classifying unit to avoid potentially estimating the model parameters with bias.

## 4.2 Measures

### Dependent Variable.

The annual salary for employees is the dependent variable. Some studies use hourly wages (Hirsch et al., 2018). Still others use weekly wages (Ruhm & Borkoski, 2003). Since I only keep full-time workers who work at least 35 hours per week and 50-52 weeks per year (reasons to be discussed later), using hourly income or annual income is just a difference in the unit. So, I use annual salary and control for work hours per week. Because I use pooled cross-sectional data in 13 years, the annual salary is converted to constant dollars based on the Consumer Price Index in 2016.  According to human capital theory, earning is a function of investment in ability measured by education and experience. Mincer (1958) found that the ability effect on earning is multiplicative rather than additive. Thus, earning is transformed to the natural logarithm.

### Independent Variables.

Commercialism is a measure on the industry level. With a focus on profit-making and cost-reduction, organizations in an industry with more commercialism behave differently from organizations in another industry with less commercialism. The degree of commercialism is thus a contextual effect. I propose four measures for commercialism.

***For-profit share of workers***. It is the percentage of for-profit workers by industry from ACS 2005-2016 and Census 2000 data[8]. Industries dominated by profit-making organizations will have more focus on efficiency. In contrast, industries dominated by nonprofit organizations have less efficiency focus and gravitate toward producing positive social externalities (Frumkin, 2002; Leete, 2001; Preston, 1989; Salamon, 1999).

The other three measures are generated from the Internal Revenue Services' (IRS) Statistics of Income (SOI) database. SOI data is the organization-level data for nonprofit organizations with detailed revenue and expense information in discrete lines. But it does not have individual-level information.

Commercialism can be defined as results of commercializing behavior – relying on commercial revenue (James, 1998), measured by the percentage of commercial revenue or the percentage of program service revenue. Commercial revenue of nonprofits stands for the conventional and classical measure of nonprofit commercialization (Child, 2010; Kerlin & Pollak, 2011; Tuckman, 1998; Weisbrod, 1998b). The Benefits Theory explains that nonprofit organizations providing public benefits rely more on donative revenue, and those providing private benefits rely more on commercial revenue (Fischer et al., 2011; Young, 2017). As such, the percentage of revenue from different sources functions to measure the nature of the goods or services that nonprofits produce (Chang & Tuckman, 1996).

***Commercial revenue***. The percentage of commercial revenue is the aggregated commercial revenue divided by the total revenue on the industry level (Child, 2010). I aggregate industry-level data in SOI data from 2000 to 2012. SOI data have somewhat different variables

[8] The data is pooled cross-sectional data. To check if there are trends in the for-profit share, I generated a variable trend: $(fpshare_{2016} - fpshare_{2000})/(\frac{fpshare_{2000}+fpshare_{2016}}{2})$. Testing trend variable in the model shows it is not significant (Model 4 in Appendix C). I dropped the trend variable.

before and after 2008. Since 2008, there are more detailed categories of commercial revenue information such as royalties, tax-exempt bonds, income from gaming, and the total number of volunteers. These categories do not exist before 2008. Following Kerlin and Pollak (2011), commercial revenue only includes program service revenue (prior year), investment income (prior year), gross rents, gross sales of inventory, and dues and assessments from members[9]. Unrelated business income is not considered because it is only around one percent or less in the aggregated total revenue.

Using revenue percentage to measure commercialism assumes the complementary relationship of donative revenue and earned income revenue. While some empirical studies find negative relationships between donative revenue and commercial revenue in human service organizations (Guo, 2006), substantial debates prevail on whether the two sources crowd in or crowd out each other (Tinkelman & Neely, 2018). Using a vector autoregression model, Weisbrod (1998a) finds that when the nonprofit goal is to cross-subsidize, commercial revenue will crowd out donative revenue. However, when the nonprofit goal is to maximize profits, commercial revenue will crowd in donative revenue, such as in universities and hospitals. If crowd-in happens, the revenue percentage may not be a good measure because the source of the increased percentage is mixed.

***Program Service Revenue (PSR).*** It is the aggregated PSR divided by the total revenue on the industry level. Classification of nonprofit revenue streams is notoriously confusing because the financial data collection tool is designed for tax purposes rather than economic analysis purposes. For instance, the purpose and mechanism of government grants are different from that of government contracts in their implications on the organization's behavior, but they

[9] https://nccs-data.urban.org/dd2.php?close=1&form=SOI+2012+990+c3

are not differentiated in the financial data. Government grants aim for the development of recipient organizations, whereas government contracts require service delivery and performance indicators (Salamon, 2002). So, government contracts involve market behavior more than government grants. As a comparison to commercial revenue, program service revenue (PSR) only includes fees and service charges and hence has a better-defined scope of revenue and becomes an alternative measure for commercializing results (Child, 2010; Foster & Bradach, 2005). Furthermore, PSR provides a more direct indication of the exchange of services, such as the scenario where hospitals depend on Medicare or Medicaid and education nonprofits rely on Head Start programs (Rose-Ackerman, 1996). Activities involving market exchange may push nonprofits to adopt business-like approaches, which is related to the change of organization behaviors.

***Fundraising Efforts.*** An additional measure is the aggregated fundraising expense divided by the total expenses on the industry level. Commercialism can also be conceptualized as the intention, defined by dictionaries. An intention to commercialize is an antecedent of the commercialization outcome associated with commercial revenue. Thus, the level of efforts invested in revenue-generating strategies might be a better indicator of organization behaviors. If an organization prioritizes generating revenue from commercial sources, it is less likely to divert a lot of efforts to a conflicting strategy for generating donative revenue through fundraising. The expense of fundraising inversely indicates the nonprofit’s intention to commercialize.

Fundraising cost is one of the three categories of expenses together with program expense and administrative expense (Hager, 2003; Krishnan, Yetman, & Yetman, 2006). The ratio of expenses has an important implication on nonprofits' efficiency and effectiveness to the eye of donors and stakeholders. High ratios of fundraising expense and administrative expenses are not desirable, but a high ratio of program expense is desirable because of their relationship with efficiency. Therefore, nonprofits have the incentive to report lower fundraising costs. Researchers continuously find empirical evidence of lower reporting of fundraising costs because lower fundraising ratio implies higher fundraising efficiency (Krishnan et al., 2006; Lecy & Searing, 2015). Underreported fundraising cost ratio might lead to overestimating the commercialism contextual effects in nonprofits. Therefore, there are pros and cons to each of the four measures for commercialism.

***Nonprofit***. In Census and ACS data, the variable "class of worker" have seven categories including self-employed, unpaid family workers, federal, state and local government workers, private worker, and nonprofit worker. I have kept categories of private workers and nonprofit categories for analysis.

***Occupation type.*** I code occupation type in three categories with the white-collar workers as the reference category. "Managerial professional" refers to the OCC1990 category of executive, administrative, and managerial occupations under the three-digit occupation classification of 003-022. OCC1990 023-391 are coded as "white-collar workers," including categories of management-related occupations, professional specialty occupations, technical, sales, and administrative support occupations. OCC1990 405-890 are coded as "blue-collar workers," including service occupations, farming, forestry, and fishing occupations, precision production, craft, and repair occupations, and operators, fabricators, and laborers.

***Female***. It is a dummy variable with female coded as 1 and male coded as 0.

**Control Variables.**

***Age and work experience.*** Learning and experience are a function of time measured by age. Age also reflects the trajectory of biological development (Mincer, 1958). Work experience is operationalized as age minus six then minus years of education. Due to their perfect collinearity, work experience is used because it is a better predictor than age for compensation study. The models also include work experience squared because wage results from diminishing returns to work experience as the work experience increases.

***Education years.*** The education attainment variable in ACS data is a variable in 24 categories with each category corresponding to certain years, and I recode it to be a continuous variable in years.

***Work hours per week***. It is a variable reported as usual hours worked per week in Census 2000 and ACS.

***Race***. It is a categorical variable coded in five dummy variables: White, Black, Latino, Asian, and other races. White is the reference group.

***English ability level***. The variable is recoded into an ordinal-level variable and treated as an interval-level variable: 1. Does not speak English; 2. Yes, but not well; 3. Yes, speak well; 4. Yes, speak only English.

***Fem_pct.*** It is the percentage of females by occupation. The female percentage is a proxy for unmeasured or unobserved personal ability and preference to adjust for estimation bias.

***Volunteer***. It is the natural log of the total number of volunteers by industry. Information of volunteers comes from the only question on the IRS 990-form: "total number of volunteers (estimate if necessary)." Volunteers are important to the nonprofit sector. Many researchers discuss how commercialism might lead to the replacement of volunteers (Lundström, 2001; Maier et al., 2016; Salamon, 1999). However, the information on volunteers is not very reliable due to the fluid definition of volunteer work (Bania & Leete, 2018). The volunteer variable only exists in 2008 and later.

*Table 1. Variables*

| | Variables | Operationalization |
|---|---|---|
| Dependent variable | Wage | Natural log of annual salary in constant dollars based on CPI in 2016 |
| Levels | Individual-level<br>Industry-level<br>Occupation-level<br>State-level | <br>38 categories<br>308 categories<br>51 categories |
| Independent variables | Commercialism (industry-level) | (1) fpshare: For-profit share of workers by industry<br>(2) commprop: Percentage of commercial revenue in total revenue<br>(3) psrprop: Percentage of PSR in total revenue<br>(4) fndrs_efft: Percentage of fundraising expense in total expense |
| | Level-1:<br>Nonprofit<br>Female<br>Managers | <br>Nonprofit=1, for-profit= 0<br>Female=1, male = 0<br>Yes=1, no= 0 |
| Control variables | Volunteers (industry-level) | The natural log of the total number of volunteers by industry |
| | Female percentage (occupation-level) | Percentage of females by occupation |
| | Level-1: | |
| | Years of education | Numeric (0 – 20) |
| | Work experience | Equal to age – education years – 6, and then squared |
| | Work hours per week | Numeric (35-99) |
| | English ability level | 1-4 from low to high |
| | Race | Dummy variables: White, Black, Latino, Asian, and Other, White is the reference group |
| | White-collar worker | Yes=1, no= 0 |
| | Blue-collar worker | Yes=1, no= 0 |

**4.3 Data**

Data used in the dissertation come from two sources. First, pooled cross-sectional data from the 5% Public Use Microdata Sample of the Census 2000, plus the American Community Survey (ACS) from 2005 to 2016, provides comprehensive information on individuals, industries, and occupations. The ACS is a mandatory survey collecting data from one-twelfth of the sample each month. It covers 3,141 counties in the 50 states, DC, and Puerto Rico ("American Community Survey Design and Methodology," 2009). Between the years 2001-2004, ACS was tested only in 36 selected counties and did not include group quarters population, covering only 800,000 addresses rather than 3 million in the full implementation.

Second, Statistics of Income (SOI) from the National Center for Charitable Statistics (NCCS) serves as the complementary dataset providing finance and revenue information for alternative measures of commercialism. SOI data are only collected from the annual filing of 990-form of nonprofit organizations. SOI data has better accuracy, but it oversamples large organizations (Kerlin & Pollak, 2011). I use the information on the industry level. So, the problem might not be as serious as used on the organizational level analysis. Since all SOI information is from nonprofit organizations, I only use measures generated from SOI for the subset of data for nonprofit workers.

**Data cleaning and summary for ACS.**

Government employees are dropped because the focus of the study is on the difference in pay between nonprofit and for-profit workers. Individuals with missing and imputed data on all relevant variables are dropped, as Census Bureau's imputation process assumes all sectors pay equally, which might level off the wage differentials between the two sectors (Bollinger, Hirsch, Hokayem, & Ziliak, forthcoming).

I restrict the analysis to full-time workers aged 16-65 who work 35 hours or above per week (Hirsch et al., 2018) and 50-52 weeks[10] per year. The restriction to full-time workers is critical to my hypothesis of altruistic motivation. Part-time workers might have several different

[10] Weeks of working per year is in 7 categories: n/a, 1-13 weeks, 14-26 weeks, 27-39 weeks, 40-47 weeks, 48-49 weeks, and 50-52 weeks.

jobs. If these jobs are from both nonprofit organizations and for-profit organizations, their multiple job holding will make their altruistic motivation ambiguous. In addition, it is likely that part-time employees have a different pension, fringe benefits, insurance plans, etc., from full-time employees. Different packages of non-wage benefits might increase or decrease the reported annual income. It is unknown whether part-time workers require higher pay because of the absence of fringe benefits or whether employers employ part-time workers just because they want to reduce the cost of fringe benefits. Cut-off at 35 hours per week and 50-52 weeks per year may reduce but cannot exclude the difference in benefit packages across sectors. Studies find that part of the negative nonprofit wage differential is due to fewer hours of nonprofit workers (Preston, 1990a; Ruhm & Borkoski, 2003). So, I control for hours of working per week.

Industries, occupations, and states are the Level-2 classification factors. ACS "indnaics" variable has a list of 268 industries[11] in major categories of agriculture, forestry, fishing and hunting (with first 2 digits of 11), mining (first 2 digits of 21), utilities (22), construction (23), manufacturing (31-33), wholesale trade (42), retail trade (44-45), transportation and warehousing (48), information and communications (51), finance, insurance, real estates (52-53), professional, scientific, management, administrative, and wage management services (54-56), educational, health and social services (61-62), art, entertainment, recreation, accommodations and food services (71-72), other services (except public administration) (81), public administration (92), activity duty military (92), and unemployed (99). Except for 92, nonprofit represents in all industries. "indnaics" starting with 813 are pure nonprofit industries with no presence of for-profits, including religious organizations, labor unions, and civic, social, advocacy organizations

[11] IPUMS code for the industry. https://usa.ipums.org/usa/volii/indcross03.shtml

and grantmaking and giving services. Excluding categories starting with 813, 92, and 99 still leaves more than 200 categories of industries.

This industry list is much longer than the list from SOI data under the NAICS[12] code. It raises the question if all observations classified as nonprofit workers in ACS really work for nonprofit organizations. For example, the industry code starting with "3" is an extensive list indicating "manufacturing," and there is no corresponding list of such categories in the SOI data. Leete (2006) reports potential misreporting of individual workers that they might not be clear about their employer's incorporation status.

Nonprofit is the tax-exempt status granted to organizations. SOI is extracted from the IRS 990 forms filed by organizations based on their tax-exempt status. So, the industry list from SOI should be more reliable than the self-reporting list from ACS. I use the SOI list to match the ACS list.

The NAICS code in SOI dataset is more standard following six-digit rule than the ACS list with various digits combining with alphabetic letters. The first two digits in the 93 categories in the SOI are 11, 22, 48, 51, 52, 54, 61, 62, 71, 81. This list from SOI is a lot more detailed but not completely corresponding to the ACS list. So, I compare the two lists and try to match as many digits as I can. During matching, I also read the industry title to make sure the correspondence between SOI and ACS lists. Some industries from ACS are combined to match

[12] 1. "NAICS is based on a production-oriented concept, meaning that it groups establishments into industries according to the similarity in the processes used to produce goods or services." It was developed for statistical purposes to classify "business establishments for the collection, tabulation, presentation, and analysis of statistical data describing the U.S. economy" (U.S. Census Bureau, 2017). 2. The first two digits designate the economic sector, the third digit designates the subsector, the fourth digit designates the industry group, the fifth digit designates the NAICS industry, and the sixth digit designates the national industry. The 5-digit NAICS code is the level at which there is comparability in code and definitions for most of the NAICS sectors across the three countries participating in NAICS (the United States, Canada, and Mexico). The 6-digit level allows for the United States, Canada, and Mexico each to have country-specific detail. More details see https://www.naics.com/what-is-a-naics-code-why-do-i-need-one/

the SOI list, and some SOI categories are combined to match ACS (Table 26 for details). Eventually, 58 ACS categories were combined into 38 analysis categories, and major combinations are for utilities, 6 categories into 1, and transportations, 9 categories into 1. The histogram of the log of income shows that the data were heavily left-skewed by a few observations. The skewness can distort the post-estimation residual diagnosis. I left truncated 819 observations with the log of income under 8 (equal to $2,981 per year) (Figure 3).

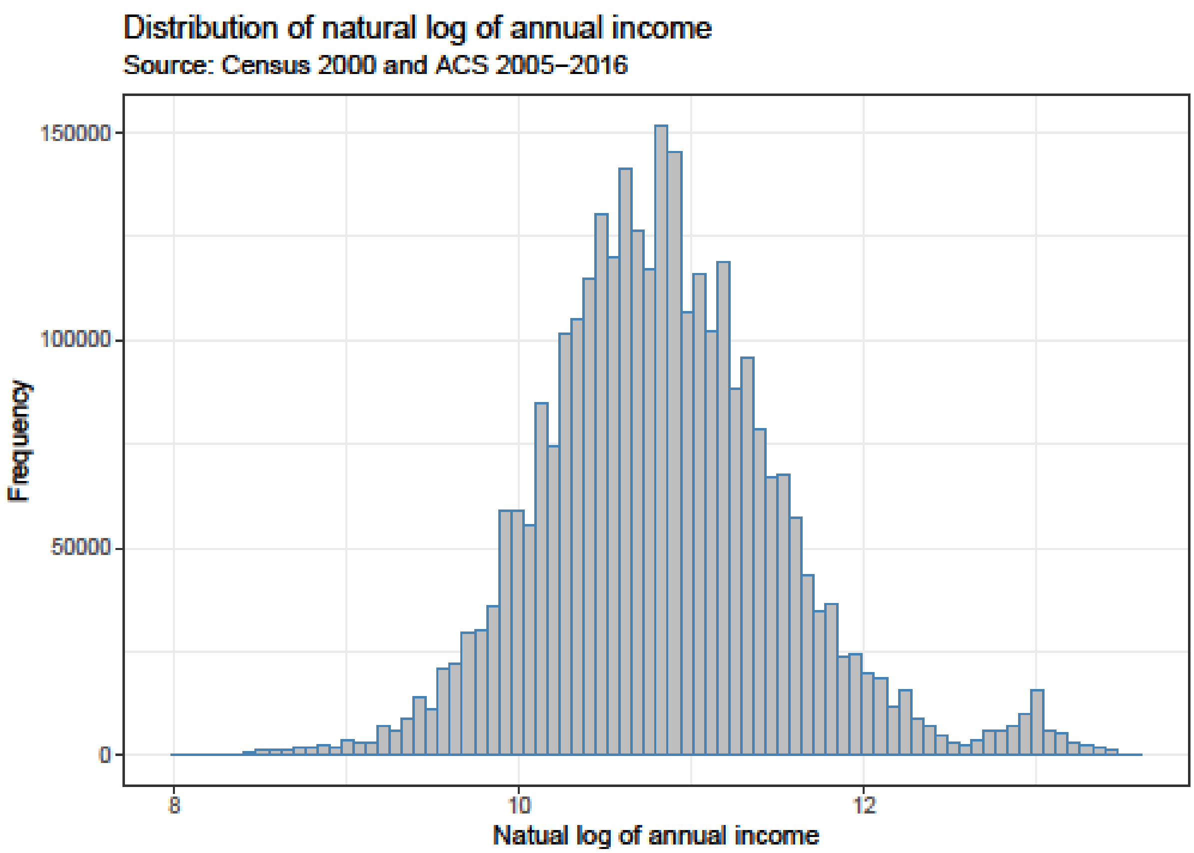


*Figure 3. Distribution of annual income*

The process leads to the final dataset with 3,017,110 observations nested in 38 industry categories and 308 occupations in 50 states and DC. Twenty-two percent of them are nonprofit workers, and 78 percent are for-profit workers (see Appendix A for dropped observations).

Table 2 shows that the size of industries and occupations is very different. In the sample, the average industry size for the nonprofit is 17,491, much smaller than that for for-profits. Similarly, the average occupation size for nonprofits is also smaller. Comparatively speaking, state difference is not as obvious as industries and occupations.

*Table 2. Descriptive statistics: observations in Level-2 categories*

| | | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Industry categories (38) | Nonprofit | 17,491 | 39,226 | 274 | 226,694 |
| | For-profit | 61,907 | 75,669 | 871 | 293,501 |
| | Total | 79,398 | 97,646 | 3,868 | 479,007 |
| Occupations (308) | Nonprofit | 2,158 | 6,287 | 1 | 78,309 |
| | For-profit | 10,082 | 15,981 | 2 | 115,120 |
| | Total | 9,796 | 20,715 | 4 | 193,429 |
| State (51) | Nonprofit | 13,032 | 13,538 | 1,129 | 57,935 |
| | For-profit | 46,127 | 50,634 | 3,026 | 248,182 |
| | Total | 59,159 | 63,514 | 4,575 | 306,100 |

Nonprofits concentrate in several narrowly defined industries. Eleven industries that employ above 10,000 nonprofit workers employ 86% of total nonprofit workers (Figure 4).

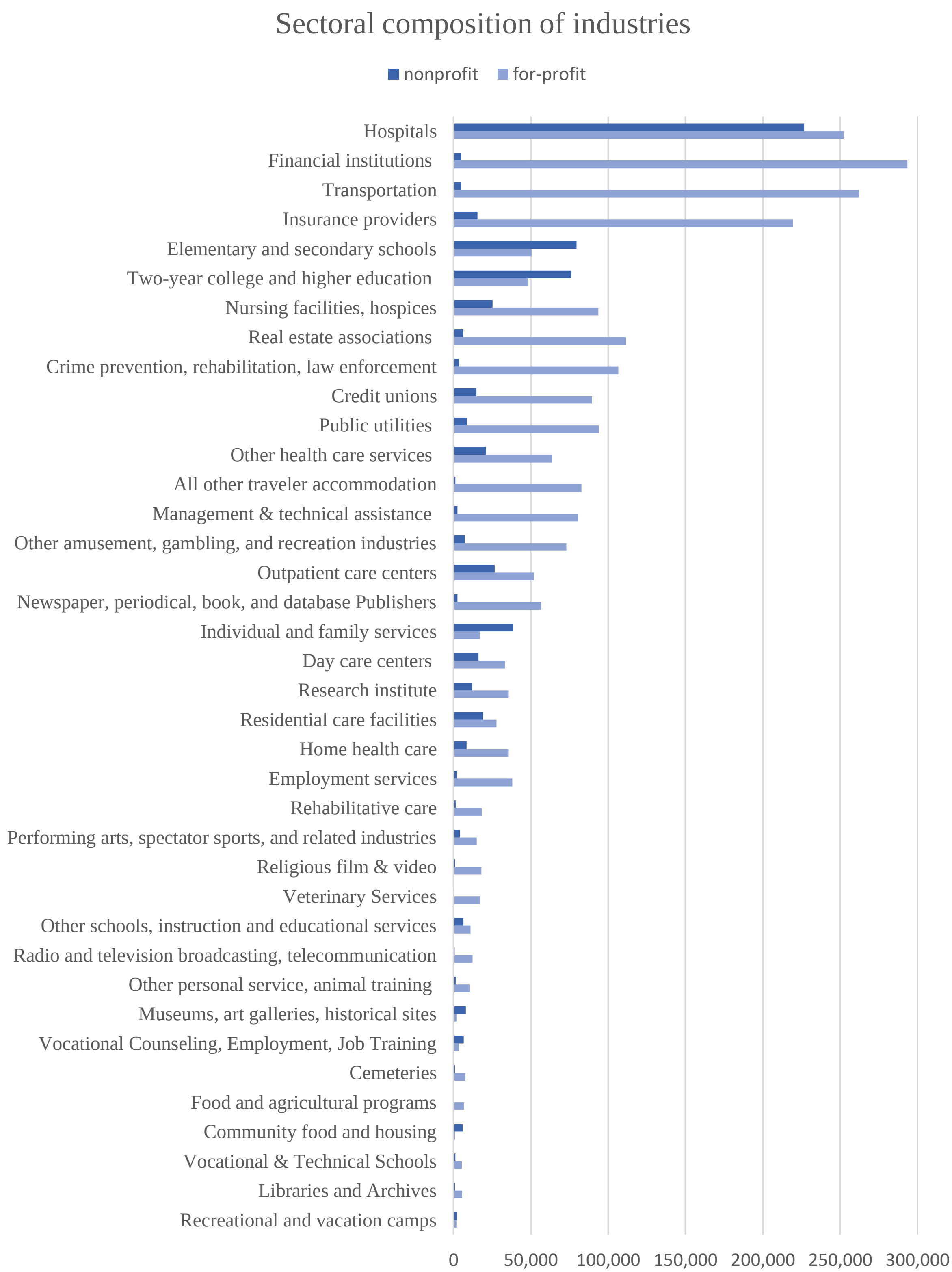


*Figure 4. Sector composition of industries*

The hospital industry (6220) alone employs 34% of nonprofit workers. Elementary and secondary schools (6111) and colleges and universities (6112) employ another 23% of nonprofit workforce, followed by individual and family services (6241), outpatient care centers (6214), nursing facilities and hospices (6231), other health care services (6219), daycare centers (6244), insurance providers (5241), credit unions (5221), and research institutes (5417). More observations by industry do not mean a higher market share.

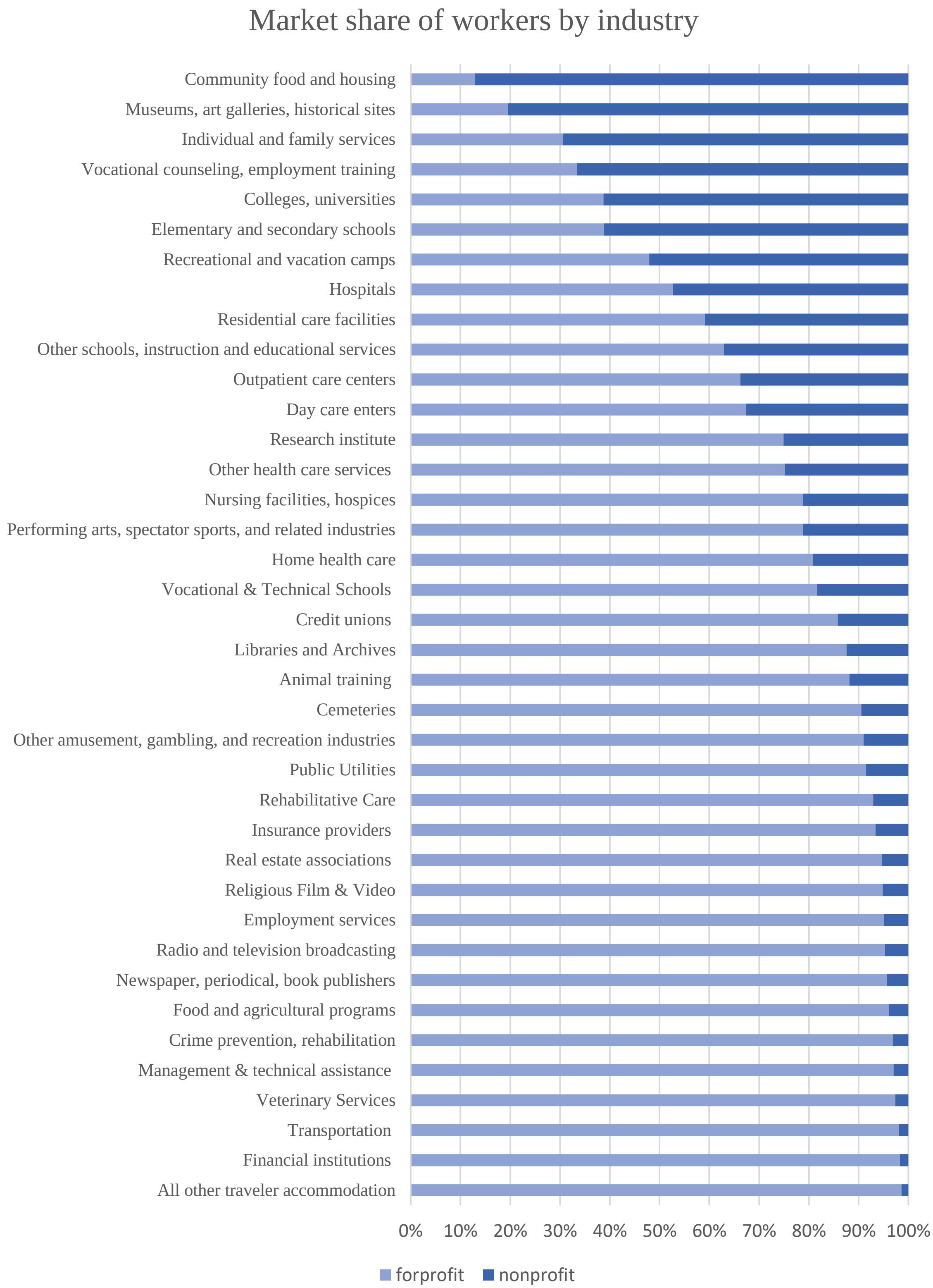


*Figure 5. Market share of workers by industry*

Figure 5 shows the market share of labor in each sector. Industries with high nonprofit share are generally small except for hospitals, elementary and secondary schools, and higher education. Seven industries with 50 percent of nonprofit share are community food and housing (6242), museums and art galleries (7121), individual and family services (6241), vocational counseling and job training (6243), elementary and secondary school (6111), two-year college and higher education (6112), and recreational and vacation camps (7212). More than half of the industries have an industry share of nonprofits under 20%.

The list for occupation categories has 320 categories in ACS data, not including the unknown and unemployment categories. After dropping industries with only for-profit or nonprofit and occupations with only males or females, there left 308 occupation categories.

Fourteen occupations with 10,000 nonprofit workers or above employ 52 percent of the total nonprofit workforce, including registered nurses, primary school teachers, subject instructors, managers, social workers, physicians, accountants. In terms of the proportion of nonprofit workers by occupation, 18 occupations have more than half of nonprofit share by occupation, including archivists and curators, clergy and religious workers, librarians, welfare service aides, secondary school teachers, social workers, managers, subject instructors, primary school teachers, psychologist, among others. Most nonprofit-dominated occupations have very high female representation. Thirty of them have 50 percent of female workers or more.

**Data cleaning and summary for SOI.**

In her economy-wide study, Leete (2001) has used the share of donative revenue (including donation and government grants) for a sample limited to corresponding industries, on the grounds that

> public-good-intensive organizations might be expected to receive both more public support of their operations as well as more labor donations. Thus, one might expect the share of the revenue from public sources (donations and government grants) to be related to donations of labor, (Leete, 2001, p. 159)

but she finds little support for the donative labor hypothesis.

Measures generated from SOI data are more pertinent to nonprofit workers than for-profit workers because the revenue and expenditure information only comes from the nonprofit part of the industry. Without information from the for-profit part of the industry, the denominators of the revenue proportion or expenditure proportion will be distorted to measure the whole industry. Table 3 shows the correlation of variables for all observations, and Table 4 is for nonprofit workers. Based on nonprofit literature, fundraising is negatively related to commercial revenue. Therefore, the relationship of annual income with the percentage of commercial revenue and percentage of PSR should also have an opposite sign with the relationship between income and fundraising efforts. Only Table (4) shows this relationship. The evidence informs my decision to subset nonprofit workers for measures generated from SOI data.

*Table 3. Pairwise correlations for all data*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (1) natural log of annual income | 1.000 | | | | | |
| (2) for-profit share of workers | 0.101* | 1.000 | | | | |
| (3) % commercial revenue | -0.036* | -0.098* | 1.000 | | | |
| (4) % program service revenue | -0.008* | -0.216* | 0.801* | 1.000 | | |
| (5) % fundraising expense | -0.057* | -0.355* | -0.409* | -0.400* | 1.000 | |
| (6) natural log of volunteer total | -0.072* | -0.754* | 0.200* | 0.169* | 0.292* | 1.000 |

* shows significance at the .01 level

*Table 4. Pairwise correlations for nonprofit worker data*

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (1) natural log of annual income | 1.000 | | | | | |
| (2) for-profit share of workers | 0.022* | 1.000 | | | | |
| (3) % commercial revenue | 0.079* | 0.353* | 1.000 | | | |
| (4) % program service revenue | 0.100* | 0.261* | 0.911* | 1.000 | | |
| (5) % fundraising expense | -0.101* | -0.496* | -0.707* | -0.704* | 1.000 | |
| (6) natural log of volunteer total | 0.098* | -0.662* | -0.008* | 0.039* | 0.104* | 1.000 |

* shows significance at the .01 level

**Descriptive statistics.**

Table (5) shows the descriptive statistics of the data with full-time workers in the dissertation. It includes more female workers than male workers. The nonprofit sector employs 68% female workers. Consistent with previous studies (Hirsch et al., 2018), the nonprofit sector employs more managerial professionals and white-collar workers than the for-profit sector. Managerial professionals are more likely to work for nonprofits, whereas blue-collar workers are less likely to work for nonprofits than for-profits. Nonprofit workers have more education and work experience and work fewer hours per week than for-profit workers. Whites are more likely, whereas Blacks, Latinos, and Asians are less likely to work for nonprofits than for-profits.

*Table 5. Descriptive statistics: demographic information across sectors*

| | Nonprofit ($n$ = 664,646) | For-profit ($n$ = 2,352,464) | Total ($n$ = 3,017,110) |
|---|---|---|---|
| Male | 32% | 44% | 41% |
| Female | 68% | 56% | 59% |
| Managerial professional | 16% | 14% | 15% |
| White-collar worker | 70% | 62% | 63% |

| | | | |
|---|---|---|---|
| Blue-collar worker | 14% | 24% | 22% |
| Years of education | 15.47 | 14.40 | 14.63 |
| Age | 44.21 | 42.24 | 42.68 |
| Work experience | 22.74 | 21.84 | 22.04 |
| Work hours per week | 43.20 | 43.99 | 43.81 |
| White | 80% | 75% | 76% |
| Black | 8% | 9% | 9% |
| Latino | 6% | 9% | 9% |
| Asian | 5% | 5% | 5% |
| Other race | 2% | 2% | 2% |

Table (6) shows the correlation of key variables. All variables are significant at the 0.01 level. The strongest correlation 0.549 is between males on the individual level and female percentage on the occupation level, followed by nonprofit on the individual level and for-profit share on the industry level. In the order of importance, years of education, work hours, male, and the female percentage have the highest impacts on the annual income.

*Table 6. Pairwise correlations (Total observation: 3, 017,110)*

| Variables | Mean | Std. Dev | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) annual income (log) | 10.83 | 0.71 | 1.000 | | | | | | | | | |
| (2) nonprofit | 0.22 | 0.41 | 0.001* | 1.000 | | | | | | | | |
| (3) male | 0.41 | 0.49 | 0.265* | -0.105* | 1.000 | | | | | | | |
| (4) years of education | 14.63 | 2.51 | 0.463* | 0.178* | 0.070* | 1.000 | | | | | | |
| (5) speak English | 3.94 | 0.30 | 0.127* | 0.048* | -0.021* | 0.208* | 1.000 | | | | | |
| (6) work experience | 22.04 | 11.83 | 0.085* | 0.031* | -0.000 | -0.259* | -0.072* | 1.000 | | | | |
| (7) experience squared | 139.94 | 139.20 | -0.197* | -0.011* | -0.033* | -0.113* | -0.034* | -0.009* | 1.000 | | | |
| (8) work hours | 43.81 | 8.07 | 0.305* | -0.040* | 0.223* | 0.154* | 0.034* | -0.014* | -0.049* | 1.000 | | |
| (9) for-profit share | 0.78 | 0.22 | 0.101* | -0.532* | 0.202* | -0.180* | -0.032* | 0.001 | -0.012* | 0.088* | 1.000 | |
| (10) female percentage | 0.59 | 0.27 | -0.241* | 0.153* | -0.549* | 0.001 | 0.032* | -0.027* | 0.034* | -0.247* | -0.311* | 1.000 |

* shows significance at the .01 level

### 4.4 Model Building and Analysis Steps

The analysis comprises four steps: linearity and normality checking; theory and hypotheses testing; residual diagnosis, and sensitivity analysis.

Cross-classified random effects modeling (CCREM) assumes multivariate normality and linearity. After cleaning the data, several variables need transformation. Annual income is transformed into the natural logarithm format. One thing to notice is the bump on the right side (Figure 3). The reason lies with the top-coded income (Table 7). Otherwise, the bump should dilute in the long tail on the right, and the distribution should look more normal.

*Table 7. Distribution of top-coded income by year*

| Year | Top-code of income | in constant dollar | # of nonprofit | # of for-profit |
|---|---|---|---|---|
| 2000 | 385,000 | 536,777 | 0 | 4 |
| 2005 | 629,000 | 773,041 | 1 | 81 |
| 2006 | 645,000 | 767,815 | 5 | 69 |
| 2007 | 666,000 | 770,951 | 5 | 73 |
| 2008 | 651,000 | 725,712 | 4 | 91 |
| 2009 | 641,000 | 717,058 | 7 | 90 |
| 2010 | 569,000 | 626,380 | 0 | 12 |
| 2011 | 607,000 | 647,589 | 1 | 12 |
| 2012 | 635,000 | 663,803 | 6 | 99 |
| 2013 | 660,000 | 688,058 | 1 | 15 |
| 2014 | 642,000 | 650,860 | 4 | 116 |
| 2015 | 658,000 | 666,315 | 8 | 116 |
| 2016 | 714,000 | 714,000 | 0 | 7 |

I use Locally Weighted Scatterplot smoothing (LOESS) to check the linearity of variables of for-profit share or workers, female percentage, and work experience. The LOESS smoothing (Jacoby, 2000) makes no assumption on the relationship of variables except for tracing the dependence of annual income on the market share. The for-profit share of workers is not strictly linear with the annual income (Appendix H). In industries with lower market share and comparatively fewer workers, it is a little curvilinear. Industries with higher for-profit share are also large industries where it shows a more linear relationship. I checked in a model with a quadratic form of market share (Model 3 in Appendix C). It was not significant. So, I treated the market share as linear.

Graphing female percentage by occupation in relation to annual earnings shows a slightly curvilinear relationship in segments of percentage between 20 percent and 40 percent (Appendix I), but the two ends display a negative relationship with the income. To make sure that my visual judgment is correct, I tested the squared term of female percentage in a model (Model 2 in Appendix C). The model shows that the squared term is not significant.

Appendix J shows an apparent and consistent quadratic relationship between work experience and the annual income, no matter whether it is in the for-profit or nonprofit sector and whether it is for males and females. Therefore, all models include work experience and its square term.

**Models.**

The model building follows the conventional multilevel modeling process. Unconditional models decomposing variance components can inform and justify the use of multilevel modeling. Based on the results of unconditional models, I run random intercept models with only fixed coefficients to understand the proportional reduction in between-group variance by the variables on Level-1 and Level-2. Then I run random coefficient models, and cross-level interaction models to test hypotheses. The subscript notation follows Beretvas (2008b), using subscript $i$ for individual, and subscripts $j1$, $j2$, and $j3$ for industry, occupation, and state, respectively. Having $j1$, $j2$, and $j3$ in the parentheses has the advantage to emphasize the parallel relationship of Level-2 factors, rather than the perception of hierarchical relationships such as subscripts $j$, $k$, and $l$.

4.4.1 Unconditional models[13]. The equation for Level-1:

$$Y_{i(j1,j2,j3)} = \beta_{0(j1,j2,j3)} + e_{i(j1,j2,j3)}, \tag{1}$$

Where

$Y_{i(j1,j2,j3)}$ is the natural log salary for person $i$ in industry $j1$, occupation $j2$, and state $j3$;

$\beta_{0(j1,j2,j3)}$ is the mean salary for workers in any combination of industry, occupation, and state;

$e_{i(j1,j2,j3)}$ is the unique effect associated with person $i$ in a certain combination of industry, occupation, and state. We assume $e_{i(j1,j2,j3)} \sim N(0, \sigma^2)$.

The variability in earnings can be attributable to industry, occupation, and state. The equation for Level-2:

[13] It is called one-way ANOVA model. It is a random effects model because the group effects are construed as random. It produces a point estimate and confidence interval for the grand mean. More importantly, it provides information about the outcome variability at different levels (Raudenbush & Bryk, 2002).

$$\beta_{0(j1,j2,j3)} = \gamma_{0000} + u_{0(j1\,)} + u_{0(\,j2)} + u_{0(j3)}$$

$$u_{0(j1)} \sim N\left(o, \tau_{0(j1)}\right),$$

$$u_{0(j2)} \sim N\left(o, \tau_{0(j2)}\right), \qquad (2)$$

$$u_{0(\,j3)} \sim N\left(o, \tau_{0(j3)}\right),$$

Where

$\gamma_{0000}$ is the grand mean salary of groups combined of industry, occupation, and state;

$u_{0(j1)}$, $u_{0(j2)}$, and $u_{0(j3)}$ is the random/unique main effect of industry $j1$, occupation $j2$, and state $j3$ on income, respectively.

Combined model:

$$Y_{i(j1,j2,j3)} = \gamma_{0000} + u_{0(j1)} + u_{0(\,j2)} + u_{0(j3)} + e_{i(j1,j2,j3)}, \qquad (3)$$

Accordingly, there are different kinds of intra-unit correlation coefficients (IUCC). The dissertation focuses on the IUCC for industries and occupations.

1) Correlation between workers in the same industry but in a different occupation and state.

$$corr\left(Y_{i(j1,j2,j3)}, Y_{i'(j1',j2,j3)}\right) = \rho_{j1} = \frac{\tau_{0(j1)}}{\tau_{0(j1)} + \tau_{0(j2)} + \tau_{0(j3)} + \sigma^2} \qquad (4)$$

2) Correlation between workers in the same occupation but in a different industry and state.

$$corr\left(Y_{i(j1,j2,j3)}, Y_{i'(j,j2',j3}\right) = \rho_{j2} = \frac{\tau_{0(j2)}}{\tau_{0(j1)} + \tau_{0(j2)} + \tau_{0(j3)} + \sigma^2} \qquad (5)$$

### 4.4.2 Models for measure 1, the for-profit share of workers.

Researchers recommend centering to avoid potential multicollinearity due to cross-level interactions and to ensure numerical stability in estimating multilevel models (Enders & Tofighi, 2007; Kreft et al., 1995; McCoach, 2010; Raudenbush & Bryk, 2002). Centering can also render the intercept more meaningful and facilitate result interpretation because it avoids the impossible values in the dataset, such as 0 percentage of for-profit labor. Except for the dependent variable, all Level-1 variables are grand-mean-centered. The grand-mean, in this case, is the mean of all observations within a combination of industry, occupation, and state. This way of centering measures how individual income deviates from the group combination of industry, occupation, and state. The for-profit share of workers by industry and the female percentage by occupation on Level-2 are also grand-mean-centered. Thus, Level-2 variables measure the contextual effect of for-profit share and femaleness. Commercialism measured as for-profit share models how the annual income changes if a person (of the same for-profit status) moves from one industry to another with a different for-profit share, holding constant individual sector status. Similarly, the female percentage measures how one's income changes from one occupation to another due to the different female percentage in these occupations holding constant individual gender status. After centering, the mean for each independent variable is close to 0 but not 0 because it takes into consideration the group size by taking the mean of the group mean.

*Table 8. Descriptive statistics (centered), (Total observations: 3,017,110)*

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Natural log of annual income | 10.83 | 0.71 | 8.00 | 13.56 |
| Nonprofit | -0.03 | 0.41 | -0.25 | 0.75 |
| Female | 0.06 | 0.49 | -0.53 | 0.47 |
| Market share by industry | 0.78 | 0.22 | -0.63 | 0.23 |

| | | | | |
|---|---|---|---|---|
| Female percentage by occupation | 0.19 | 0.27 | -0.38 | 0.59 |
| White | -0.02 | 0.43 | -0.78 | 0.22 |
| Black | 0.00 | 0.28 | -0.09 | 0.91 |
| Latino | 0.01 | 0.28 | -0.07 | 0.93 |
| Asian | 0.02 | 0.22 | -0.04 | 0.96 |
| Other race | -0.01 | 0.14 | -0.03 | 0.97 |
| Managers | 0.06 | 0.35 | -0.09 | 0.91 |
| White-collar workers | 0.03 | 0.48 | -0.61 | 0.39 |
| Blue-collar workers | -0.09 | 0.41 | -0.31 | 0.69 |
| Work experience | -0.24 | 11.83 | -28.29 | 36.71 |
| Experience squared | 1.40 | 1.39 | 0.00 | 13.48 |
| Years of education | 0.31 | 2.51 | -14.32 | 5.68 |
| Work hours | 0.49 | 7.72 | -8.00 | 55.00 |
| English speaking level | -0.02 | 0.14 | -2.00 | 0.00 |

(1) To test Hypothesis 1 that nonprofit workers earn less than for-profit workers on average, I use a random slope model (equations 6 and 7) to partial out the random variation of nonprofit pay differential on industry and occupation levels. The nonprofit pay coefficient $\beta_{1(j1,j2,j3)}$ is specified to have a probability distribution on industry and occupation levels (equation 7). The coefficient $\gamma_{1000}$ in equation (7) is thus the partially pooled nonprofit wage differential showing that on average, whether nonprofit workers earn more or less than the for-profit workers. To test Hypotheses 2 of commercialism effects on pay, I need to control all Level-1 variables (equation 6), the female percentage by occupation, and state effects. The coefficient of $\gamma_{0100}$ in equation (7) will indicate whether commercialism increases or decreases the annual pay.

Level-1 equation:

$$Y_{i(j1,j2,j3)} = \beta_{0(j1,j2,j3)} + \beta_{1(j1,j2,j3)} nonprofit_{i(j1,j2,j3)} +$$

$$\beta_{2(j1,j2,k3)} female_{i(j1,j2,j3)} + \sum_{n=3}^{11} \beta_{n(j1,j2,j3)} X_{ni(j1,j2,j3)} + e_{i(j1,j2,j3)}, \quad (6)$$

$$e_{i(j1,j2,j3)} \sim N(0, \sigma^2)$$

Level-2 equation:

$$\beta_{0(j1,j2,j3)} = \gamma_{0000} + \gamma_{0100} fpshare_{j1} + \gamma_{0200} fem\_pct_{j2} + r_{0(j1)} + r_{0(j2)}$$
$$+ r_{0(j3)}$$

$$\beta_{1(j1,j2,j3)} = \gamma_{1000} + r_{1(j1)} + r_{1(j2)}$$

$$\beta_{2(j1j2,j3)} = \gamma_{2000} \quad (7)$$

$$\beta_{3(j1j2,j3)} = \gamma_{3000}$$

$$\vdots$$

$$\beta_{11(j1,j2,j3)} = \gamma_{11000}$$

Where

$r_{0(j1)}$ and $r_{1(j1)}$ are residuals of the random intercept and random slope on the industry level;

$r_{0(j2)}$ and $r_{1(j2)}$ are residuals of the random intercept and random slope on the occupation level;

$r_{0(j3)}$ is the residual of random intercept on the state level;

*X* is a vector for control variables, including gender, years of education, work experience, and its squared term, hours of working per week, race, and English-speaking level.

(2) To test Hypothesis 3, the Level-1 equation (6) remains the same, and the Level-2 equation is specified in equation (8). It shows how the Level-2 variable commercialism moderates the nonprofit wage differential. The coefficient $\gamma_{1100}$ is for Hypothesis 3.

Level-2 equation:

$$\begin{aligned}
\beta_{0(j1,j2,j3)} &= \gamma_{0000} + \gamma_{0100} fpshare_{j1} + \gamma_{0200} fem_prop_{j2} + r_{0(j1)} + r_{0(j2)} \\
&\quad + r_{0(j3)} \\
\beta_{1(j1,j2,j3)} &= \gamma_{1000} + \gamma_{1100} fpshare_{j1} + r_{1(j1)} + r_{1(j2)} \\
\beta_{2(j1j2,j3)} &= \gamma_{2000} \\
\beta_{3(j1j2,j3)} &= \gamma_{3000} \\
&\vdots \\
\beta_{11(j1,j2,j3)} &= \gamma_{11000}
\end{aligned} \tag{8}$$

(3) To test Hypothesis 4 that commercialism increases the manager-staff pay gap, the Level-1 equation is equation (9) by adding interaction between nonprofit and occupation type to equation (6). The Level-2 equation is specified in equation (10). The coefficients of $\gamma_{12100}$ and $\gamma_{13100}$ in equation (10) are for hypothesis 3, showing the three-way interaction between commercialism, nonprofit, and occupation type.

Level-1 equation:

$$Y_{i(j1,j2,j3)} = \beta_{0(j1,j2,j3)} + \beta_{1(j1,j2,j3)} nonprofit_{i(j1,j2,j3)} + \beta_{2(j1,j2,j3)} female_{i(j1,j2,j3)} + \sum_{n=3}^{11} \beta_{n(j1,j2,j3)} X_{ni(j1,j2,j3)} + \beta_{12(j1,j2,j3)} nonprofit_{i(j1,j2,j3)} * mngprof_{i(j1,j2,j3)} + \beta_{13(j1,j2,j3)} nonprofit_{i(j1,j2,j3)} * bluecol_{i(j1,j2,j3)} + e_{i(j1,j2,j3)}, \quad e_{i(j1,j2,j3)} \sim N(0, \sigma^2) \tag{9}$$

Level-2 equation:

$$\begin{aligned}
\beta_{0(j1,j2,j3)} &= \gamma_{0000} + \gamma_{0100} fpshare_{j1} + r_{0(j1)} + r_{0(j2)} + r_{0(j3)} \\
\beta_{1(j1,j2,j3)} &= \gamma_{1000} + r_{1(j1)} + r_{1(j2)} \\
\beta_{2(j1j2,j3)} &= \gamma_{2000} \\
\beta_{3(j1j2,j3)} &= \gamma_{3000} \\
&\vdots \\
\beta_{11(j1,j2,j3)} &= \gamma_{11000} \\
\beta_{12(j1,j2,j3)} &= \gamma_{12000} + \gamma_{12100} fpshare_{j1} \\
\beta_{13(j1,j2,j3)} &= \gamma_{13000} + \gamma_{13100} fpshare_{j1}
\end{aligned} \tag{10}$$

(4) To test Hypotheses 5 that commercialism increases the gender pay gap, I add interaction between nonprofit and female (equation 11). The Level-2 equation is specified in equation (12). The coefficient of $\gamma_{14100}$ is for Hypothesis 5.

Level-1 equation:

$$Y_{i(j1,j2,j3)} = \beta_{0(j1,j2,j3)} + \beta_{1(j1,j2,j3)} nonprofit_{i(j1,j2,j3)} + \beta_{2(j1,j2,j3)} female_{i(j1,j2,j3)} + \sum_{n=3}^{11} \beta_{n(j1,j2,j3)} X_{ni(j1,j2,j3)} + \beta_{14(j1,j2,j3)} nonprofit_{i(j1,j2,j3)} * female_{i(j1,j2,j3)} + e_{i(j1,j2,j3)}, \quad e_{i(j1,j2,j3)} \sim N(0, \sigma^2) \tag{11}$$

Level-2 equation:

$$\begin{aligned}
\beta_{0(j1,j2,j3)} &= \gamma_{0000} + \gamma_{0100} fpshare_{j1} + \gamma_{0200} fem_pct_{j2} + r_{0(j1)} + r_{0(j2)} + r_{0(j3)} \\
\beta_{1(j1,j2,j3)} &= \gamma_{1000} + r_{1(j1)} + r_{1(j2)} \\
\beta_{2(j1 j2,j3)} &= \gamma_{2000} \\
\beta_{3(j1 j2,j3)} &= \gamma_{3000} \\
&\vdots \\
\beta_{11(j1,j2,j3)} &= \gamma_{11000} \\
\beta_{14(j1,j2,j3)} &= \gamma_{14000} + \gamma_{14100} fpshare_{j1}
\end{aligned} \tag{12}$$

### 4.4.3 Models for measures 2-4: percentage of commercial revenue, percentage of program service revenue, and fundraising efforts.

The dataset used in this part of the analysis is restricted to nonprofit workers based on the correlation table information as well as previous study findings (Leete, 2001). With the subset of data, I slightly revise models by deleting the nonprofit variable. Therefore, models in this part do not tell the sectoral pay differential. Rather, they are random intercept models testing if commercialism increases the annual earnings of nonprofit employees and if commercialism increases the manager-staff pay gap and the gender pay gap in the nonprofit sector.

### 4.4.4 Sensitivity analysis:

I have done two sets of sensitivity analyses to test if the estimate for nonprofit wage differential is consistent and robust. The first set is altering the structures on level-2, including modeling nonprofit random slope on the interaction level of industry and occupation, and the state level. The industry-occupation interaction level is used because there might be a correlation between industries and occupations. For instance, physicians are more likely to appear in the hospital industry than other industries like vocational training or public utilities; the subject instructor occupation is more likely to appear in universities or colleges than credit unions. Besides, previous research used industry-occupation interactions in other modeling approaches (Faulk et al., 2012; Leete, 2001). The state-level is meant for control, and no empirical evidence suggests that the sectoral pay differential varies across the state level. So, I do not plan to run random slope models on the state level for hypothesis testing, but I do it as part of the sensitivity test to make sure it does not bring dramatic changes to the fixed coefficient.

The second set is altering datasets. The first comparison dataset is Census 2000 because it is for one year and with the sample size larger than other single-year data. The second comparison dataset is the overall dataset but dropping hospitals and higher education industries based on the advice from Kerlin and Pollak (2011) and Foster and Bradach (2005). They argue that these two industries have long, stable, and high-level commercial revenue with a long history, which makes them outliers. In the third comparison dataset, I use the original 58 industry categories from the ACS.

# Chapter V. Analysis and Results

This chapter presents the analysis and modeling results based on model specifications in Chapter Four. I present my findings in the following order: variance components, hypothesis testing, assumption checking, sensitivity analysis, and random effects for nonprofit wage differential. I used the "lme4" package in R (Bates et al., 2018; Roberts & Bates, 2010). Cross-classified models are conceptually straightforward, but its computation is demanding. Roberts and Bates (2010) introduce that "lme4" utilizes sparse matrix theory and Cholesky decomposition to solve the problem of memory and time needed for computing. All models use Restricted Maximum Likelihood[14] (REML) parameter estimation strategy (Beretvas, 2008a; McCoach, 2010) because REML estimates of variance components adjust for uncertainty in fixed effect estimates (Raudenbush & Bryk, 2002). So, it can better handle the unbalanced data: the size of the industry in the dataset ranges from 3,868 to 479,007 with a mean of 79,398, and the size of the occupation ranges from 4 to 193,429 with a mean of 9,796 (Table 2). Output tables are formatted through the stargazer package (Hlavac, 2018).

## 5.1 Intra Unit Correlation Coefficients (IUCC)

Multilevel modeling starts with the unconditional model with no predictors to analyze the variance between the groups. By decomposing variance components, the unconditional model produces "a point estimate and confidence interval for the grand means" (Raudenbush & Bryk, 2002, p. 24) on different levels or groups (industry, occupation, and state). The IUCC is the ratio

[14] In multilevel models, "the distribution of Y [the dependent variable] is assumed to be normal, with a mean depending on the regression coefficients and a dispersion depending on the variance components. These are the parameters that are estimated by the corresponding technique, which is simply called maximum likelihood, but sometimes also full maximum likelihood. Alternatively, we can apply the principle of maximum likelihood to the least-squares residuals. This is known as restricted or residual maximum likelihood, or REML. It means we first remove the effect of the fixed variables: remember that the residuals are uncorrelated with all the fixed variables in the model. The distribution of the residuals is also normal, because computing residuals from Y just involves taking weighted sums. But the distribution of the residuals no longer depends on the estimates of the fixed effects, it only depends on the variance components" (Kreft & Leeuw, 1998, pp 131-133).

of the between-group variability to the total variability based on the unconditional model (Raudenbush & Bryk, 2002). A large IUCC means that groups are very heterogeneous and group effects are salient and cannot be ignored. Thus, IUCC can inform whether multilevel modeling is justified.

To understand the outcome variability on different levels, I ran unconditional models with different combinations of Level-2 factors (Table 9). The constant is the grand mean of log of annual income. Estimated as an optimally weighted average of the sample means from Level-2 units, the grand mean is the weighted least squares estimate for the mean salary of Level-2 unit combinations. The IUCC in the square brackets is the proportion of variance in the outcome explained on different levels, holding other levels constant.

*Table 9. Unconditional Models*

| | **Variance and proportion on each unit** | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Industry | 0.08784[15]<br>[16.83%] | | 0.03537<br>[7.69%] | 0.03353<br>[7.33%] | |
| Industry × Year | | | | | 0.03563<br>[7.77%] |
| Occupation | | 0.1626<br>[34.51%] | 0.12937<br>[28.11%] | 0.12664<br>[27.67%] | 0.12620<br>[27.54%] |
| State | | | | 0.01265<br>[2.76%] | 0.01272<br>[2.78%] |
| Residual | 0.43401[16] | 0.3086 | 0.29543 | 0.28486 | 0.28377 |
| Constant | 10.725***<br>(223.039) | 10.727***<br>(464.072) | 10.634***<br>(288.649) | 10.589***<br>(269.161) | 10.586***<br>(388.870) |

[15] This is "parameter variance": the variance of the true group salary around the grand mean.
[16] This is "error variance."

| | | | | | |
|---|---|---|---|---|---|
| Observations | 3,017,110 | 3,017,110 | 3,017,110 | 3,017,110 | 3,017,110 |
| Akaike Inf. Crit. | 6,044,203 | 5,017,487 | 4,885,728 | 4,776,157 | 4,767,070 |
| Bayesian Inf. Crit. | 6,044,242 | 5,017,526 | 4,885,780 | 4,776,222 | 4,767,135 |
| *Note:* | 1. $^{*}$p$^{**}$p$^{***}$p<0.01; 2. IUCC in square brackets; 3. T-statistics in parentheses. | | | | |

The observations in the dataset nest in 38 industries, 308 occupations, and 50 states and the District of Columbia. Accordingly, there are variance and residuals from each of the three sources. Model (1) uses the industry as the Level-2 factor. It shows that 17 percent of the variability in annual earnings is attributable to industries without including any predictors. The 0.08784 is the variance on the industry level, quantifying the heterogeneity of industry mean wages. Thus, the standard deviation of the industry sample mean is 0.30[17], which means the industry with the highest mean salary is expected to be 11.31[18], equivalent to $81,634. The industry with the lowest estimated mean salary is 10.14[19], equivalent to $25,336. Therefore, industries are very different in their average salaries.

Similarly, Model (2) with the occupation as the Level-2 factor shows that occupation explains 35 percent of the variance in the annual income. The occupation with the highest mean salary is estimated to be 11.52, and the lowest-paying occupation is 9.94, with a difference of $79,768 annually. Model (3), with the industry and occupation as identifiers on the Level-2, shows that variability on the industry level is reduced by 9 percentage points, and variability on the occupation level is reduced by 6 percentage points. It indicates that some occupations are

[17] $\sqrt{0.08784}$
[18] $10.725 + 1.96 \times \sqrt{0.08784}$
[19] $10.725 - 1.96 \times \sqrt{0.08784}$

more likely to appear in some industries than others. Comparing Models (1) to (3) suggests that neglecting either industry or occupation will result in spurious effects (Beretvas, 2008b). Model (4) adds states to the Level-2. The 3 percent variance associated with the state indicates that partialling out the variance on the industry and occupation levels, the annual income of employees varies across states but not very much. The pure state effect between the highest-paying state and the lowest-paying state is $17,646. Also, the state as the additional factor has very little effect on the variability on industry and occupation levels. Despite the small variance, Model (4) provides a better fit based on the information criteria[20]. The dataset is pooled from 13 years. There might be the possibility that the industry changes in these many years. Model (5) performs a safety check whether the time is related to the variability of the annual income, and the result shows that the time effect is negligible. Therefore, Model (4) with industry, occupation, and state on Level-2 is selected as the base model for the following models.

Based on Model (4), the weighted least squares estimate for the grand-mean salary is 10.589 ($39,396) conditional on the between-group (industry, occupation, state) effects. Given the variance of 0.3353 on the industry level, the range of the estimated industry mean salary is between 10.23 and 10.95[21] after partialling out the variability on occupation and state levels. The variance of 0.12664 on the occupation level suggests that the range of the occupation mean salary is estimated to be between 9.89 and 11.29[22] , holding industry and state effects constant.

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[20] Akaike Information Criteria (AIC) provides a means for model selection. AIC estimates the relative amount of information lost by a given model: the less information a model loses, the higher the quality of that model. In estimating the amount of information lost by a model, AIC deals with the trade-off between the goodness of fit of the model and the parsimony of the model. Both Bayesian Information Criteria (BIC) and AIC attempt to resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC (Burnham & Anderson, 2004).

[21] $10.589 \pm 1.96 * \sqrt{0.03353}$

[22] $10.589 \pm 1.96 * \sqrt{0.12664}$

Similarly, excluding industry and occupation effect, the state mean salary is estimated to be between 10.37 and 10.81[23].

**5.2 Hypotheses Testing: Measure 1 (for-profit share of workers)**

The first measure for commercialism is the for-profit share of workers computed based on Census 2000 and 2005-2016 ACS. To test hypotheses 1 and 2, I first assessed how much variance is reduced by Level-2 variables (Model 6), and how much is reduced by the full model with all Level-1 variables (Model 8). The reduced proportion of variance measures how well the predictors explain the outcome, just like $R^2$ in OLS models. Then, the random slope (or random coefficient) of the nonprofit is added on industry and occupation levels to test the two hypotheses. The random slope is not considered on the state level because no empirical evidence indicates nonprofit wage differential variability on the state level, and the unconditional model shows that overall variability on the state level is limited.

**Testing Hypothesis 1.**

In fitting the models, I multiplied for-profit share of workers and the female percentage by 100 to facilitate interpretation. I also rescaled experience squared by dividing 100. All nominal-level variables are dummy coded.

Level-2 variables in Model (6) reduce the variance by 20 percent[24] on the industry level and 2 percent[25] on the occupation level. It means that for-profit share accounts for some variability on the industry level, but the female percentage variable barely explains occupation variability despite its statistical significance. Level-1 variables reduce the variance by 28 percent on the industry level and 56 percent on the occupation level (Model 7). So, variability on the

[23] $10.589 \pm 1.96 * \sqrt{0.01265}$
[24] (0.03353 – 0.02683) / 0.03353
[25] (0.12664 – 0.12395) / 0.12664

occupation is more related to individual-level variables. All variables on both levels explain 50 percent[26] of industry variability and 57 percent[27] of occupation variability.

***Effects of nonprofit as altruistic motivation (Hypothesis 1).***

To test the hypothesis that nonprofit full-time workers earn less than for-profit full-time workers, one can ignore or include variability of the nonprofit wage differential on the industry and occupation levels. Models (6) to (8) are random intercept models assuming that no predictors randomly vary on industry and occupation levels.

Alternatively, Model (9), the random slope model, specifies nonprofit to vary across industries and occupations based on existing empirical findings (Handy & Katz, 1998; King & Lewis, 2017; Leete, 2001; Preston, 1988; Ruhm & Borkoski, 2003; Weisbrod, 1983). It estimates the random effects of nonprofit wage differential, which means that the nonprofit wage differential is different across industries and occupations. Other variables might also vary across industries and occupations, but due to the parsimonious caution on the model convergence as well as the theoretical interest of nonprofit, other variables are constrained to the mean in the model.

Model (8) and Model (9) are the same except for the random effects of nonprofit. The constant 10.682 in Model (8) is the estimated annual income for a person with an average condition on all variables after removing group differences of industry, occupation, and state. Model (8) assumes all variables have constant and common effects in all industries, occupations, and states (Raudenbush & Bryk, 2002). For instance, women earn 19 percent less than comparable men, and an additional year in education increases annual salary by 7 percent in all

[26] (0.03353 - 0.01661) / 0.03353
[27] (0.12664 - 0.05426) / 0.12664

industries, occupations, and states. In other words, it assumes all industries and occupations are not different in the effects of the predictors.

Under this assumption, nonprofit workers earn 0.2 percent more than comparable for-profit workers. The result is consistent with previous economy-wide studies (Hirsch et al., 2018; Leete, 2001; Ruhm & Borkoski, 2003). However, it is not consistent with other studies. Studies on discrete industries (Ben-Ner et al., 2011; Holtmann & Idson, 1993; Mocan & Tekin, 2003; Preston, 1988) or occupations (King & Lewis, 2017; Preston, 1989; Weisbrod, 1983) find divergent results of nonprofit wage differentials. Leete (2001) also makes it clear that nonprofit wage differential varies across industries.

*Table 10. Testing Hypotheses 1 and 2.*

| | **Natural log of annual income** | | | |
|---|---|---|---|---|
| **Fixed effects part** | **(6)** | **(7)** | **(8)** | **(9)** |
| For-profit share of workers | $0.003^{***}$ | | $0.004^{***}$ | $0.003^{***}$ |
| | (3.199) | | (4.213) | (3.537) |
| Female percentage | $-0.002^{***}$ | | -0.001 | -0.001 |
| | (-2.678) | | (-1.521) | (-1.445) |
| Nonprofit | | $0.002^{***}$ | $0.002^{***}$ | $-0.057^{***}$ |
| | | (2.868) | (2.891) | (-3.893) |
| Female | | $-0.187^{***}$ | $-0.187^{***}$ | $-0.185^{***}$ |
| | | (-276.110) | (-276.068) | (-272.933) |
| Years of education | | $0.073^{***}$ | $0.073^{***}$ | $0.073^{***}$ |
| | | (469.254) | (469.262) | (468.674) |
| Latino | | $-0.065^{***}$ | $-0.065^{***}$ | $-0.063^{***}$ |
| | | (-58.415) | (-58.414) | (-57.061) |

| | | | | |
|---|---|---|---|---|
| Black | | -0.095*** | -0.095*** | -0.093*** |
| | | (-92.223) | (-92.220) | (-90.402) |
| Asian | | -0.030*** | -0.030*** | -0.029*** |
| | | (-22.175) | (-22.173) | (-21.799) |
| Other races | | -0.067*** | -0.067*** | -0.066*** |
| | | (-32.827) | (-32.827) | (-32.353) |
| Speak English | | 0.046*** | 0.046*** | 0.045*** |
| | | (44.992) | (44.993) | (44.654) |
| Work experience | | 0.011*** | 0.011*** | 0.011*** |
| | | (448.688) | (448.690) | (449.153) |
| Work experience squared | | -0.053*** | -0.053*** | -0.053*** |
| | | (-267.027) | (-267.026) | (-266.867) |
| Work hours per week | | 0.013*** | 0.013*** | 0.013*** |
| | | (345.043) | (345.041) | (342.442) |
| Constant | 10.590*** | 10.682*** | 10.682*** | 10.673*** |
| | (286.868) | (331.190) | (368.283) | (374.288) |
| **Random effects part** | | **Variance** | | |
| Industry (Intercept) | 0.02683 | 0.02413 | 0.01661 | 0.015718 |
| Nonprofit | | | | 0.006896 |
| Occupation (Intercept) | 0.12395 | 0.05456 | 0.05426 | 0.052737 |
| Nonprofit | | | | 0.005739 |
| State (intercept) | 0.01265 | 0.01140 | 0.01140 | 0.011391 |
| Residual | 0.28486 | 0.22603 | 0.22603 | 0.225067 |
| Observations | 3,017,110 | 3,017,110 | 3,017,110 | 3,017,110 |
| Akaike Inf. Crit. | 4,776,169 | 4,078,156 | 4,078,169 | 4,066,108 |
| Bayesian Inf. Crit. | 4,776,260 | 4,078,363 | 4,078,401 | 4,066,393 |
| *Note:* | | | | *p**p***p<0.01 |

Thus, the assumption that nonprofit wage differential is constant across industries and occupations is questionable. Model (9)[28] specifies the nonprofit coefficient to randomly vary over Level-2 industries and occupations without the attempt to predict this variation (Raudenbush & Bryk, 2002, p. 26).

In Model (9), both the intercept and slope of nonprofit vary randomly across industries and occupations. The random effects of nonprofit wage differential are illustrated as fixed effects[29] in addition to its random variation on industry and occupation levels. The fixed effects and random effects for nonprofit are expressed in equation (7) from Chapter 4: $\beta_{1(j1,j2,j3)} = \gamma_{1000} + r_{1(j1)} + r_{1(j2)}$, which means that the nonprofit wage differential is composed of group-invariant effect $\gamma_{1000}$, industry-variant effects $r_{1(j1)}$, and occupation-variant effects $r_{1(j2)}$. Untangling the fixed coefficient and random effects makes it possible to develop a theoretical understanding of nonprofit pay.

Corresponding to my theoretical argument and hypothesis, the group-invariant effect refers to the donative labor effect because altruistic motivation is part of human nature. Altruistic workers tend to select to work for nonprofits. Group-variant effects are effects caused by industries and occupations. Model (9) shows that the donative labor effect leads nonprofit workers to earn 5.5[30] percent less than the comparable for-profit workers partialling out the industry effect and occupation effect. The negative 5.5 percent translates into a difference of

[28] To check if random slope improves model fitting, I performed a Chi-squared test. The result suggests that having random slope of nonprofit in the model significantly reduces the residual sum of squares (Appendix F).
[29] "The label fixed effects is reserved for multilevel modeling estimates that are constant across L2 units, and the label random effects is used to denote the model estimates that vary across L2 units" (Aguinis, Gottfredson, & Culpepper, 2013, p. 1497).
[30] $(e^{-0.057} - 1) \times 100$

$2,392 annually. The result confirms Hypothesis 1, where nonprofit workers donate their labor to the employer by accepting lower pay due to their altruistic motivation.

The random effects part in Table (10) displays the variance components. In Model (8), 0.01661 is the variance of intercept, meaning that after controlling for all variables, occupation, and state effects, wage dispersion on the industry level follows a probability distribution with a mean of 0 and variance of 0.01661. Similarly, wage dispersion on the occupation level follows a probability distribution with a mean of 0 and a variance of 0.05426 after controlling all other variables in the model. In comparison, Model (9) has a random intercept with a mean of 0 and a variance of 0.015718, representing the dispersion of industry mean salaries excluding occupation and state effects. Model (9) produces random slopes of nonprofit with mean of 0 and variance of 0.006896 on the industry level, representing the variability of cross-sector wage differential on the industry level after controlling for the fixed part, occupation, and state effects. Similarly, on the occupation level, the variability of the intercept is 0.052373, and the variability of the nonprofit slope is 0.005739. The random effects for nonprofit range across industries and occupations, and they are best illustrated through plotting. I elaborate on the random effects after completing all hypothesis tests.

**Testing Hypothesis 2.**

Hypothesis 2 examines the effect of commercialism (the industry-level variable) on pay (the individual-level variable). The first measure of commercialism, the percentage of for-profit workers by industry, is derived mathematically as a compositional effect (Diez Roux, 2002) in contrast to other measures of commercialism. Compositional effect means that the group-level variable adds "incremental prediction to an individual outcome," above the beyond the individual-level predictors (Hofmann & Gavin, 1998).

Coefficients for Level-2 variables are quite similar in Model (8) and Model (9). The for-profit share of workers measures commercialism and efficiency. The coefficients show that more commercialized industries pay higher than less commercialized ones. As the for-profit share of workers increases by 1 percentage point, the income increases by 0.3 percent[31] (Model 9), which is around $129. In the dataset, the range of for-profit market share is 85.63 percentage points. The expected difference in average salary between industries with the highest and lowest of the for-profit share of workers is $10,475[32] , holding other variables constant. The results confirm Hypothesis 2, where commercialism increases workers' annual income. By being in an industry with a higher for-profit share of workers, one can earn more than a comparable peer in an industry with a lower for-profit share of workers.

**Testing Hypothesis 3.**

Hypothesis 3 examines the cross-level interaction effect of whether commercialism explains the variability of nonprofit pay differential on the industry level. A cross-level interaction occurs "when the random slope of a level-1 predictor is predicted by a level-2 predictor" (Preacher, Curran, & Bauer, 2006, p. 441). The cross-level interaction can only apply when the random effects of nonprofit are present. If the variance of nonprofit slopes (0.006896 in Model 9) were not different from zero, cross-level interaction should not be conducted (Aguinis, Gottfredson, & Culpepper, 2013). Therefore, the model is also built based on Model (9) of random coefficients. Equation (13) combines equations (6) and (8), and the coefficient $\gamma_{1100}$ is

[31] $(e^{0.003} - 1) \times 100$

[32] The range for market share after centering ranges from -62.79 to 22.84. Therefore, the difference is $e^{10.673+22.84\times0.003} - e^{10.673-62.79\times0.003}$

what needs to test hypothesis 3. The focal variable is nonprofit differential, and the moderator is commercialism.

$$\begin{aligned} Y_{i(j1,j2,j3)} = \gamma_{0000} + \gamma_{0100} fpshare_{j1} + \gamma_{0200} fem\_pct_{j2} \\ + \gamma_{1000} nonprofit_{i(j1,j2,j3)} \\ + \gamma_{1100} fpshare_{j1} nonprofit_{i(j1,j2,j3)} \\ + \beta_{2(j1,j2,k3)} female_{i(j1,j2,j3)} + \sum_{n=3}^{11} \beta_{n(j1,j2,j3)} X_{ni(j1,j2,j3)} \\ + (r_{1(j1)} + r_{1(j2)}) nonprofit_{i(j1,j2,j3)} + r_{0(j1)} + r_{0(j2)} + r_{0(j3)} \\ + e_{i(j1,j2,j3)} \end{aligned} \tag{13}$$

On Level-2, each industry has a specific random intercept and a random slope. Random slopes of nonprofit on the industry and occupation levels show that for each industry and occupation, the nonprofit wage differential is different after controlling all variables and Level-2 factors. The random intercepts are the unexplained but explicit parts on the corresponding levels to demonstrate the inter-industry and inter-occupation wage differentials (Aguinis et al., 2013).

The cross-level interaction indicates that the industry pay advantage for nonprofits depends on the for-profit share of workers. In Model (10), a 1 percentage point increase in commercialism increases the annual pay by 0.3 percent for for-profit workers, but the increase for nonprofit workers is only 0.2 percent. In other words, in nonprofit dominant industries, nonprofits have industry pay advantage, and in for-profit dominant industries, for-profits have industry pay advantage.

Based on the hypothesis, organizations in nonprofit dominant industries are less likely to generate a surplus from commercial revenue than for-profits dominant industries. Due to the concern of social goal and service quality, nonprofit organizations charge less for services than for-profits. In addition, nonprofits face more scrutiny and less autonomy than nonprofits in disposing of the surplus. All of these contribute to the differentiated effect of commercialism on pay between for-profit and nonprofit.

*Table 11. Testing Hypothesis 3*

| **Fixed effects part** | **Natural log of annual income (10)** |
|---|---|
| For-profit share of workers | 0.003*** |
| | (3.890) |
| Nonprofit | -0.057*** |
| | (-4.099) |
| Female percentage by occupation | -0.001 |
| | (-1.447) |
| Female | -0.185*** |
| | (-272.933) |
| Years of education | 0.073*** |
| | (468.672) |
| Latino | -0.063*** |
| | (-57.059) |
| Black | -0.093*** |
| | (-90.399) |
| Asian | -0.029*** |
| | (-21.798) |
| Other races | -0.066*** |
| | (-32.352) |
| Speak English | 0.045*** |
| | (44.653) |

| | |
|---|---|
| Work experience | $0.011^{***}$ |
| | (449.154) |
| Work experience squared | $-0.053^{***}$ |
| | (-266.867) |
| Work hours per week | $0.013^{***}$ |
| | (342.442) |
| For-profit share of workers × nonprofit | $-0.001^{**}$ |
| | (-2.350) |
| Constant | $10.673^{***}$ |
| | (374.580) |
| **Random effects part** | **Variance** |
| Industry (Intercept) | 0.015671 |
| Nonprofit | 0.006122 |
| Occupation (Intercept) | 0.052733 |
| Nonprofit | 0.005735 |
| State (intercept) | 0.011388 |
| Residual | 0.225067 |
| Observations | 3,017,110 |
| Akaike Inf. Crit. | 4,066,118 |
| Bayesian Inf. Crit. | 4,066,415 |
| *Note:* t-statistics in parentheses | $^{*}p^{**}p^{***}p<0.01$ |

**Testing Hypothesis 4.**

Hypothesis 4 examines the moderating effect of commercialism on the manager-staff pay gap. It is expected that commercialism increases the pay of managers more than non-managerial staff. The models are built based on Model (9) with random intercepts on the state, industry, and occupation levels, and random slopes of nonprofit on industry and occupation levels.

In Model (11), managerial professionals earn 22 percent more than white-collar workers and 46 percent more than blue-collar workers, holding other variables and Level-2 variability constant. Model (12) shows that the pay gap between managers and non-managerial staff is narrower than the for-profit sector, although it is not statistically significant. This result does not contradict previous findings that managers donate more than other workers in the nonprofit sector (clerical workers in Preston, 1989). The reason is that industry and occupation differences have been removed from the fixed coefficient estimate in Model (12).

Model (13) explores a variety of scenarios among occupation type (manager, white-collar worker, blue-collar worker), sector difference, and commercialism effect. The manager is the focal variable (Jaccard & Turrisi, 2003), nonprofit is the first-order moderator, and commercialism is the second-order moderator. Although minimal, the moderating effects of commercialism on the occupation pay gap and sectoral-occupation pay gap are significant.

The first-order moderating effects show that the nonprofit pay is more equitable (though not significant) because the high-earning managers get less pay (-0.017), and the low-earning blue-collar workers get more pay (0.011) in the nonprofit sector than the for-profit sector. The second-order moderating effects, that is, the commercialism effects, show that in more commercialized industries, nonprofit managers get even lower pay (-0.0003), and nonprofit blue-collar workers get even higher pay (0.001). It means that the sectoral wage gap for managers is larger than the sectoral wage gap for blue-collar workers in more commercialized industries.

*Table 12. Testing hypothesis 4*

| | **Natural log of annual income** |
|---|---|

| Fixed effects part | (11) | (12) | (13) |
|---|---|---|---|
| For-profit share of workers | 0.003*** | 0.003*** | 0.003*** |
| | (3.538) | (3.537) | (3.951) |
| Nonprofit | -0.058*** | -0.059*** | -0.058*** |
| | (-3.999) | (-4.055) | (-4.254) |
| Manager | 0.220*** | 0.224*** | 0.223*** |
| | (3.744) | (3.684) | (3.676) |
| Blue-collar worker | -0.243*** | -0.248*** | -0.244*** |
| | (-9.586) | (-9.632) | (-9.480) |
| Female | -0.185*** | -0.185*** | -0.185*** |
| | (-272.947) | (-272.942) | (-272.826) |
| Female percentage by occupation | -0.003*** | -0.003*** | -0.003*** |
| | (-6.377) | (-6.379) | (-6.368) |
| Years of education | 0.073*** | 0.073*** | 0.073*** |
| | (468.590) | (468.589) | (468.362) |
| Latino | -0.063*** | -0.063*** | -0.063*** |
| | (-57.057) | (-57.055) | (-56.996) |
| Black | -0.093*** | -0.093*** | -0.093*** |
| | (-90.395) | (-90.394) | (-90.374) |
| Asian | -0.029*** | -0.029*** | -0.029*** |
| | (-21.794) | (-21.796) | (-21.808) |
| Other races | -0.066*** | -0.066*** | -0.066*** |
| | (-32.352) | (-32.352) | (-32.352) |
| Speak English | 0.045*** | 0.045*** | 0.045*** |
| | (44.647) | (44.641) | (44.445) |
| Work experience | 0.011*** | 0.011*** | 0.011*** |
| | (449.153) | (449.152) | (448.933) |
| Work experience squared | -0.053*** | -0.053*** | -0.053*** |
| | (-266.866) | (-266.868) | (-266.876) |

| | | | |
|---|---|---|---|
| Work hours per week | 0.013*** | 0.013*** | 0.013*** |
| | (342.437) | (342.438) | (342.449) |
| For-profit share of workers × nonprofit | | | -0.001** |
| | | | (-2.276) |
| For-profit share of workers × manager | | | -0.0005*** |
| | | | (-7.217) |
| Nonprofit × manager | | -0.005 | -0.017 |
| | | (-0.212) | (-0.695) |
| For-profit share of workers × blue-collar | | | -0.0003*** |
| | | | (-5.685) |
| Nonprofit × blue-collar | | 0.012 | 0.011 |
| | | (1.111) | (0.977) |
| For-profit share of workers × nonprofit × manager | | | -0.0003** |
| | | | (-2.317) |
| For-profit share of workers × nonprofit × blue-collar | | | 0.001*** |
| | | | (5.223) |
| Constant | 10.725*** | 10.726*** | 10.726*** |
| | (382.494) | (382.250) | (382.584) |
| **Random effects part** | | **Variance** | |
| Industry (Intercept) | 0.015712 | 0.015712 | 0.015653 |
| Nonprofit | 0.006909 | 0.006907 | 0.005972 |
| Occupation (Intercept) | 0.037703 | 0.037714 | 0.037756 |
| Nonprofit | 0.005742 | 0.005762 | 0.005800 |
| State (intercept) | 0.011392 | 0.011389 | 0.011391 |
| Residual | 0.225067 | 0.225067 | 0.225058 |
| Observations | 3,017,110 | 3,017,110 | 3,017,110 |
| Akaike Inf. Crit. | 4,066,020 | 4,066,035 | 4,066,990 |
| Bayesian Inf. Crit. | 4,066,330 | 4,066,371 | 4,066,390 |
| *Note:* | | | *p**p***p<0.01 |

To facilitate the understanding of the coefficients, I graph three scenarios: low market share, medium market share, and high market share of for-profit workers (Figure 6). Commercialism increases the wage for all three groups, but the increasing rates for managers and white-collar workers are lower than that for blue-collar workers. The differing effect leads to a larger sector pay gap for managers and white-collar workers in for-profit dominant industries. Therefore, Hypothesis 4, commercialism increases the pay of managers more than for non-managerial workers is not supported.

Two potential explanations might account for the disagreement between the hypothesis and findings. The tax-exempt status of nonprofits does not allow exorbitant salaries (Hallock, 2000; Hansmann, 1980). Managers are a high-earning group, and the increase in their salary is more sensitive than blue-collar and white-collar workers in nonprofit organizations. The other reason might relate to the donate labor theory. Even in for-profit dominant industries where managerial professionals are more valued, altruistically motivated managers might choose to work for nonprofits at a pay lower than comparable for-profit managers.

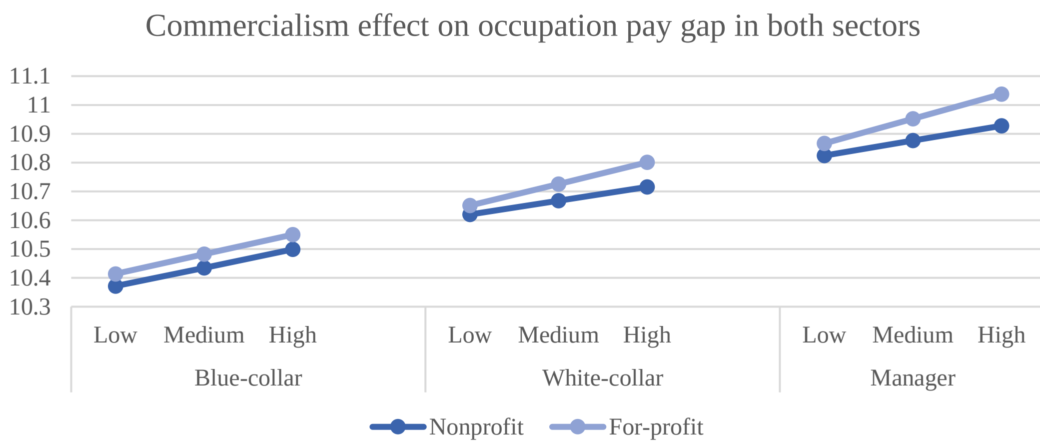



*Figure 6. Commercialism effect on occupation types*

**Testing Hypothesis 5.**

Hypothesis 5 examines the moderating effect of commercialism on the gender pay gap in both sectors. It is expected to increase the pay of men more than women. The correlation coefficients in Table (6) suggest a composition effect of gender pay in the nonprofit sector. Nonprofit is negatively related to male (-0.105) and positively related to the female percentage (0.153), which means men are less likely to be nonprofit workers and nonprofits have larger female worker populations. Furthermore, commercialism is negatively related to the female percentage (-0.311).

The models are also built based on Model (9) with the same random intercepts and random slopes. Overall, females earn 19 percent less than comparable males (Model 9). A supplementary analysis[33] of gender random effects on both industry and occupation levels shows that some industries and occupations are more women-friendly than others. However, due to the large size of the fixed coefficient of females, even in women-friendly industries and occupations,

[33] The separate supplementary analysis is not included in the dissertation.

women still earn less than men. Model (14) shows that the gender pay gap is smaller in the nonprofit sector by 7 percentage points than the for-profit sector. In Model (15) of the three-way interaction, the focal variable is female, the first order moderator is nonprofit, and the second-order moderator is commercialism. The first-order moderating effect shows more gender-pay equity in the nonprofit sector (0.039). The second-order moderating effect shows that in more commercialized industries, gender equity in nonprofit is strengthened (0.001). Furthermore, women in more commercialized industries are paid less than less commercialized industries.

*Table 13. Testing hypothesis 5*

| | Natural log of annual income | | |
|---|---|---|---|
| **Fixed effects part** | **(9)** | **(14)** | **(15)** |
| For-profit share of workers | 0.003*** | 0.003*** | 0.003*** |
| | (3.537) | (3.597) | (4.028) |
| Female percentage | -0.001 | -0.001** | -0.001** |
| | (-1.445) | (-2.217) | (-2.129) |
| Nonprofit | -0.057*** | -0.054*** | -0.051*** |
| | (-3.893) | (-3.760) | (-3.687) |
| Female | -0.185*** | -0.183*** | -0.173*** |
| | (-272.933) | (-269.322) | (-214.237) |
| Years of education | 0.073*** | 0.073*** | 0.073*** |
| | (468.674) | (467.849) | (466.470) |
| Latino | -0.063*** | -0.063*** | -0.063*** |
| | (-57.061) | (-57.133) | (-57.234) |
| Black | -0.093*** | -0.093*** | -0.092*** |
| | (-90.402) | (-90.203) | (-89.762) |
| Asian | -0.029*** | -0.029*** | -0.028*** |

| | | | |
|---|---|---|---|
| | (-21.799) | (-21.681) | (-21.142) |
| Other races | -0.066*** | -0.065*** | -0.065*** |
| | (-32.353) | (-32.248) | (-32.095) |
| Speak English | 0.045*** | 0.045*** | 0.046*** |
| | (44.654) | (44.703) | (44.952) |
| Work experience | 0.011*** | 0.011*** | 0.011*** |
| | (449.153) | (449.437) | (449.442) |
| Work experience squared | -0.053*** | -0.053*** | -0.053*** |
| | (-266.867) | (-267.199) | (-267.573) |
| Work hours per week | 0.013*** | 0.013*** | 0.013*** |
| | (342.442) | (341.999) | (341.448) |
| For-profit share of workers × nonprofit | | | -0.001** |
| | | | (-2.391) |
| For-profit share of workers × female | | | -0.002*** |
| | | | (-51.135) |
| Nonprofit × female | | 0.074*** | 0.039*** |
| | | (46.178) | (18.376) |
| For-profit share of workers × nonprofit × female | | | 0.001*** |
| | | | (16.166) |
| Constant | 10.673*** | 10.672*** | 10.670*** |
| | (374.288) | (374.360) | (374.942) |
| **Random effects part** | | **Variance** | |
| Industry (Intercept) | 0.015718 | 0.015704 | 0.015594 |
| Nonprofit | 0.006896 | 0.006578 | 0.005992 |
| Occupation (Intercept) | 0.052737 | 0.052813 | 0.052851 |
| Nonprofit | 0.005739 | 0.006171 | 0.006003 |
| State (intercept) | 0.011391 | 0.011376 | 0.011368 |
| Residual | 0.225067 | 0.224907 | 0.224695 |
| Observations | 3,017,110 | 3,017,110 | 3,017,110 |

| | | | |
|---|---|---|---|
| Akaike Inf. Crit. | 4,066,108 | 4,063,990 | 4,061,180 |
| Bayesian Inf. Crit. | 4,066,393 | 4,064,287 | 4,061,516 |
| *Note:* | | | $^{*}$p$^{**}$p$^{***}$p<0.01 |

Similarly, I graph three scenarios to facilitate the interpretation of the results: low, medium, and high for-profit share of workers (Figure 7). Commercialism increases the gender pay gap for both sectors. The commercialism effect is smaller in the nonprofit sector than in the for-profit sector, leading to a larger sector pay gap, which supports Hypothesis 5.

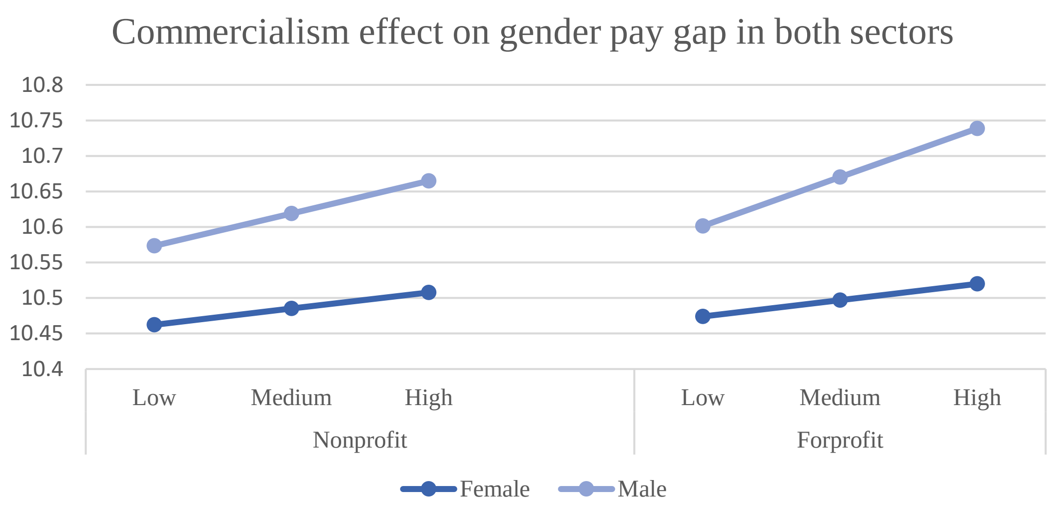



*Figure 7. Commercialism effect on gender pay gap*

**5.3 Assumption checking.**

Multilevel models are an integrated analysis of variance and regression analysis based on several assumptions, including correct functional form, normality, independent observations and errors, and constant variance of residuals. Violating these assumptions may result in misrepresentation of the relationship among variables or invalid hypothesis tests.

In terms of functional forms, I have checked linearity using LOESS smoothing for several variables and decided to use the quadratic form for work experience in the models. Here are several diagnostic plots for assumptions related to residuals based on Model (9). First, Level-1 residuals are assumed to be normally distributed and have a zero mean (Figure 8).

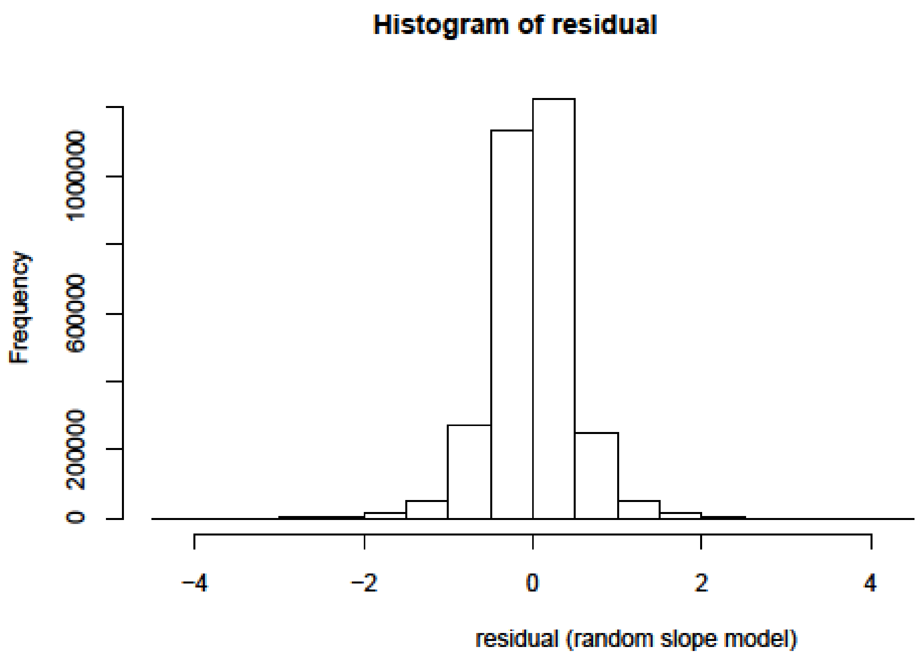



*Figure 8. Histogram of Level-1 residuals: normal distribution*

Figure 9 is the normal quantile-quantile plot based on the actual residuals divided by their theoretical quantiles. The plot is approximately linear, showing that the residual is almost normally distributed.

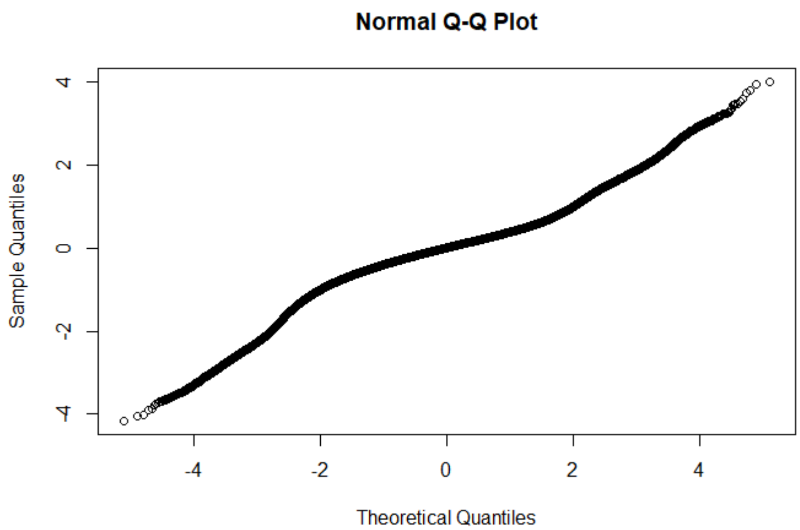



*Figure 9. Level-1 residual normality*

Secondly, Level-2 residuals are assumed to be multivariate normal and also have means of zero. Level-2 diagnosis is more problematic. The residual of random intercept on the industry level is normally distributed (Figures 10), but the residual of random slope shows that industries are heavily right-skewed because all the plots are above the diagonal line (Figure 11). The reason is that nonprofits only concentrate in several narrowly defined industries. To understand how the estimate changes, I have done more analyses by segmenting the dataset into dataset (1) with for-profit under 60% (9 industries), dataset (2) with for-profit share under 86% (18 industries), and dataset (3) with for-profit share over 86% (20 industries). The results show that there is a donative labor effect for nonprofit workers except for the dataset for the top 9 industries dominated by nonprofits where the donative labor effect is not significant (Appendix G). Table 31 highlights the importance of industrial heterogeneity in affecting workers' annual income.

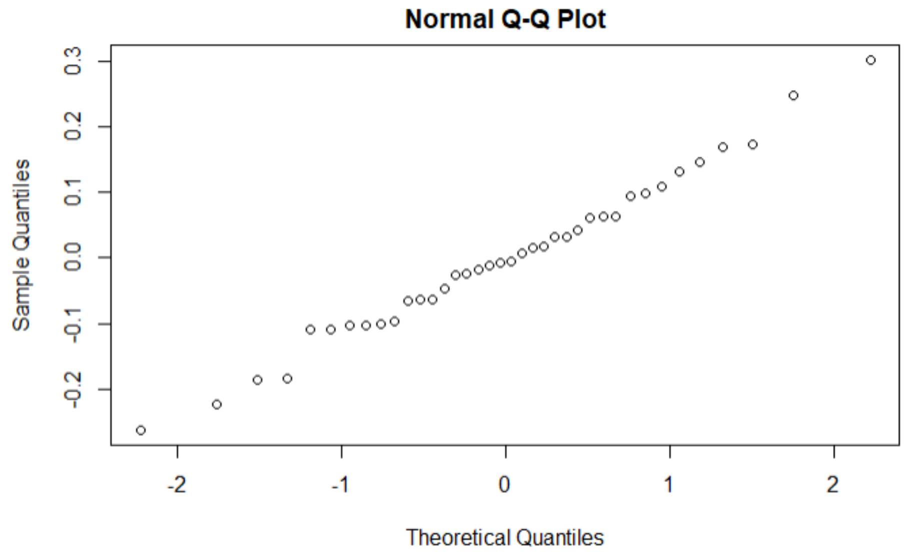



*Figure 10. Residual normality of random intercept on the industry level*

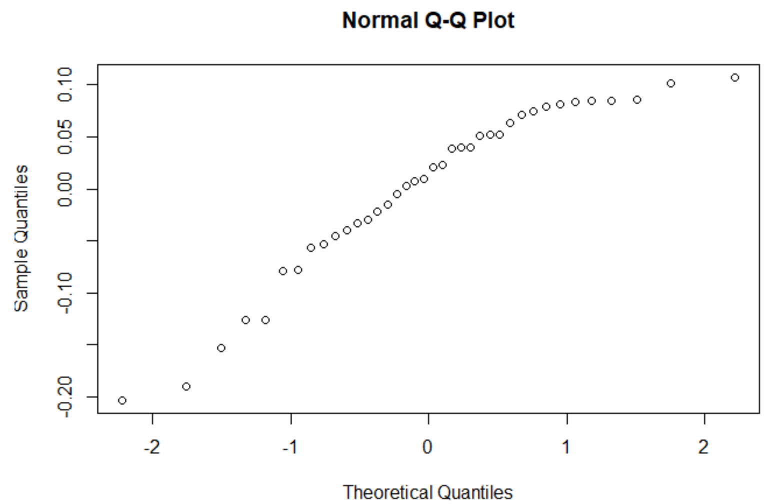



*Figure 11. Residual normality of random slope on the industry level*

Figures (12) shows the constant variance of residuals on the industry level.

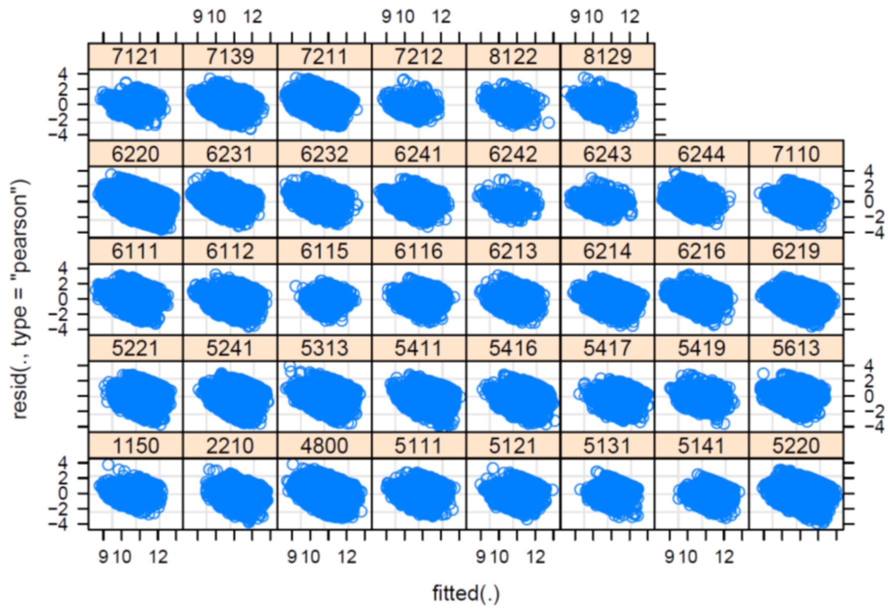



*Figure 12. Standardized residuals versus fitted value by industry*

Comparing to the industry level, the distribution of residuals on the occupation level is quite normal, except for a few outliers (Figure 13).

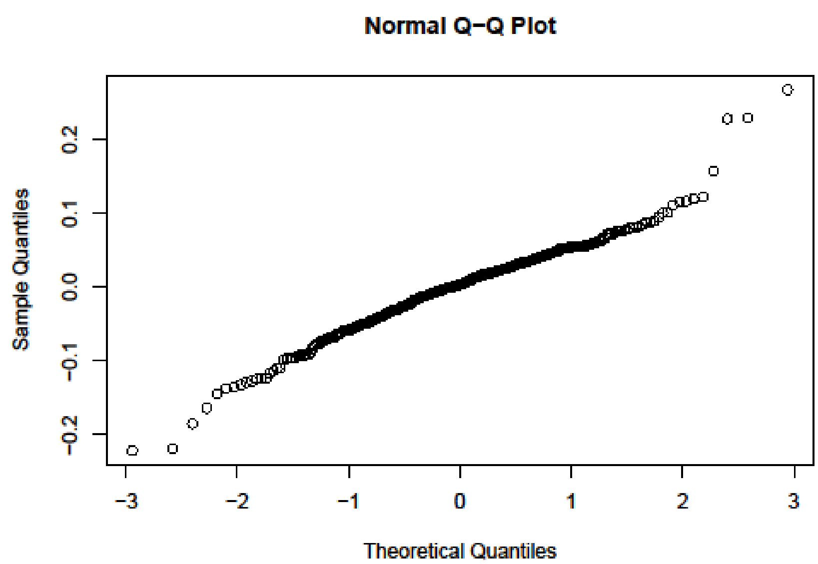



*Figure 13. Level-2 residual normality on the occupation level*

### 5.4 Random effects of the nonprofit wage differential.

Previous empirical studies of discrete industries and occupations indicate that nonprofit pay differential varies across industries and occupations. Random effects of nonprofit wage differential are the random slopes for the nonprofit variable specified on the industry and occupation levels. On the industry level, $r_{0(j1)}$ and $r_{1(j1)}$ in equation (7) represent intercepts and slopes, respectively. Their dispersions are quantified as the variance, which corresponds to 0.015718 and 0.006898 in Model (9). On the occupation level, $r_{0(j2)}$ and $r_{1(j2)}$ represent intercepts and slopes. Their variances are 0.052737 and 0.005739, respectively. The state-level only has random intercepts. So, I will not discuss it.

#### ***Random effects of nonprofit on the industry level.***

Model (9), the full model with all predictors and nonprofit random effects on Level-2, produces the unbiased and efficient estimates for all specified variables excluding effects from industry, occupation, and state levels. Fixed coefficients are used to test the hypotheses. The random effects of nonprofit are the residuals of nonprofit on industry and occupation levels controlling for all the variables in the model, Level-1 errors, and the state-level effects.

R allows extracting the exact values for all intercepts and slopes, presented in Appendices D and E together with the for-profit share of workers and the female percentage by occupation. Caterpillar plot (Figures 13 and 14) is usually used to compare random-effect parameters and demonstrate the variability of the fixed coefficient. The more observations in each category, the shorter the error bar is around the point estimate.

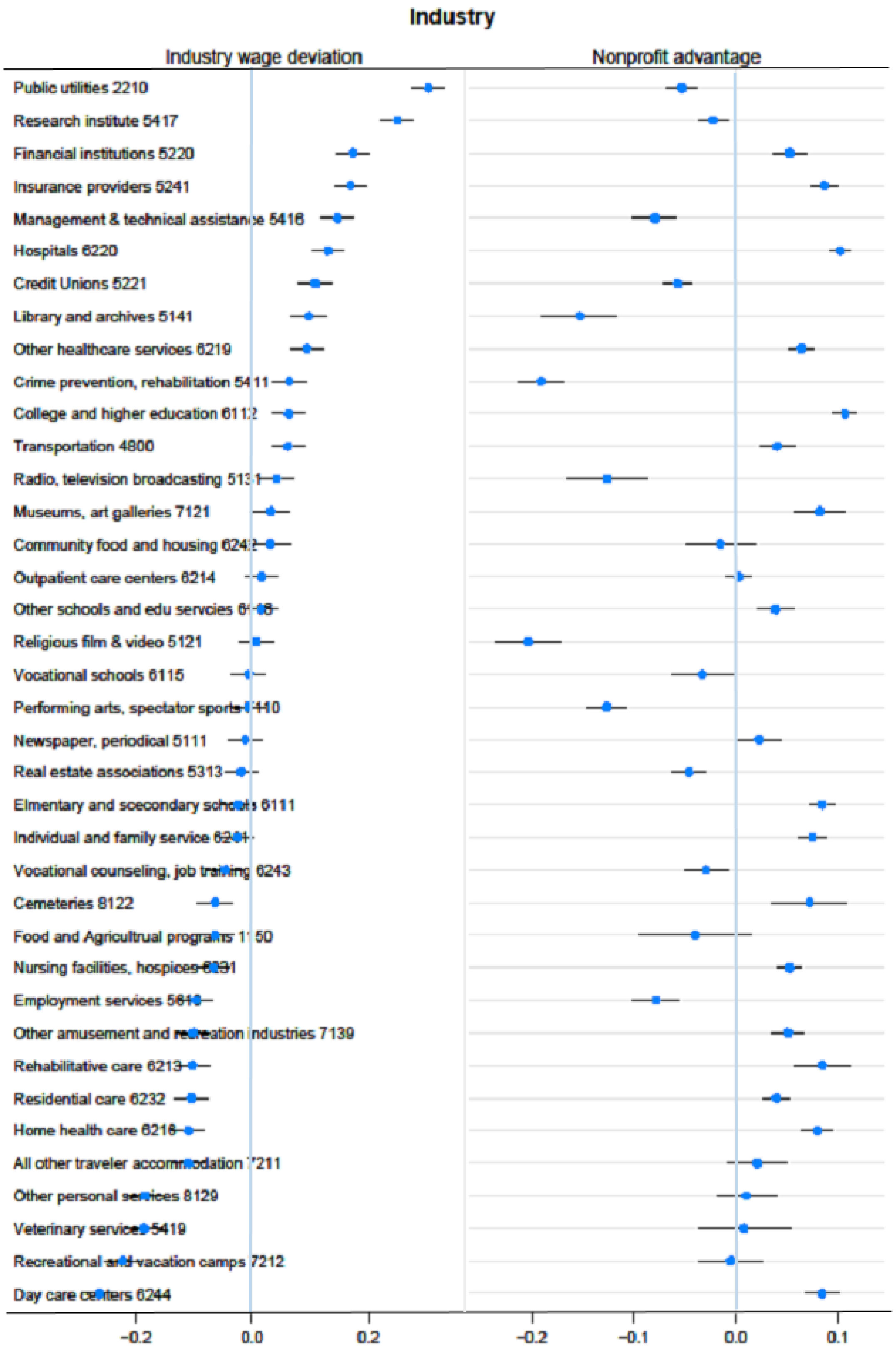



*Figure 14. Random effects of nonprofit pay differential on the industry level*

On the industry level, the random intercepts (left panel in Figure 14) is the residual variability of the industry wage. They show how much each industry deviates from the constant (10.673) in the model. The random slopes (right panel on Figure 14) are the differences in sectoral pay differential on the industry level, holding constant the occupation effect. It indicates how much each industry deviates from the fixed coefficient for nonprofit (-0.057).

The public utility industry (2210) has the highest industry-level pay. The predicted annual earning for an average white male for-profit worker in the public utility industry is 10.973 (10.673+0.3) (Appendix D), net of occupation and state effects.  Nonprofits have an industry disadvantage of negative 5.4 percent in this industry. Together with the donative labor effects, a nonprofit worker earns 11 percent less than a comparable for-profit worker in this industry, conditional on occupation pay differences.

Child daycare services (6244) is the lowest-paying industry. An average white male for-profit worker in this industry is expected to earn 10.413 (10.673-0.26), net of occupation and state effects.  Nonprofit has 8 percent industry advantage in child daycare services. A nonprofit worker is expected to earn 2.3 percent (-0.057+0.08) more than a for-profit worker in this industry, conditional on occupation pay differences.

The following industries have the largest industry disadvantage for nonprofits: religious film and video (5121) with 20 percent less than the for-profit, crime prevention (5411) with negative 19 percent, libraries and archives (5141) with negative 15 percent, performing arts and spectator sports (7110) and radio and television broadcasting (5131) with negative 13 percent. These are industry disadvantages in addition to the negative 5.7 percent donative labor effect, excluding the occupation effect.

On the other end, the following industries have the largest industry advantage in pay for nonprofits: college and universities (6112) and hospitals (6220) over 10 percent industry advantage for nonprofits; insurance providers (5241), rehabilitative care (6213), elementary and secondary schools (6111), daycare centers (6244), and museums and art galleries (7121) have over 8 percent. These are industry advantages in addition to a negative 5.7 percent donative labor effect, excluding the occupation effect.

***Random effects of nonprofit on the occupation level.***

The variance of the random intercept on the occupation level is 0.052737, and the variance of the nonprofit random slope is 0.005739 (Model 9). The left panel on Figure (15) shows how much the occupation wage deviates from the constant, holding constant all variables, industry and state effects. The right panel shows the sectoral pay differential on the occupation level, controlling for the industry effect.

In detail, around 70 occupations have almost no sectoral pay difference (-0.01 to 0.01), and 206 occupations have the nonprofit wage differential between -0.05 and 0.05 in addition to the fixed coefficient of -0.057, net of the industry effect. There are several outliers. The occupation with the largest occupation advantage for nonprofit workers is musicians or composers (occupation code:186). Musicians have a 27 percent occupation pay advantage for nonprofits over for-profits. Adding altruistic motivation effect and occupation advantage together, nonprofit musicians earn 21.3 (27-5.7) more than comparable for-profit musicians, conditional on the industry effects.

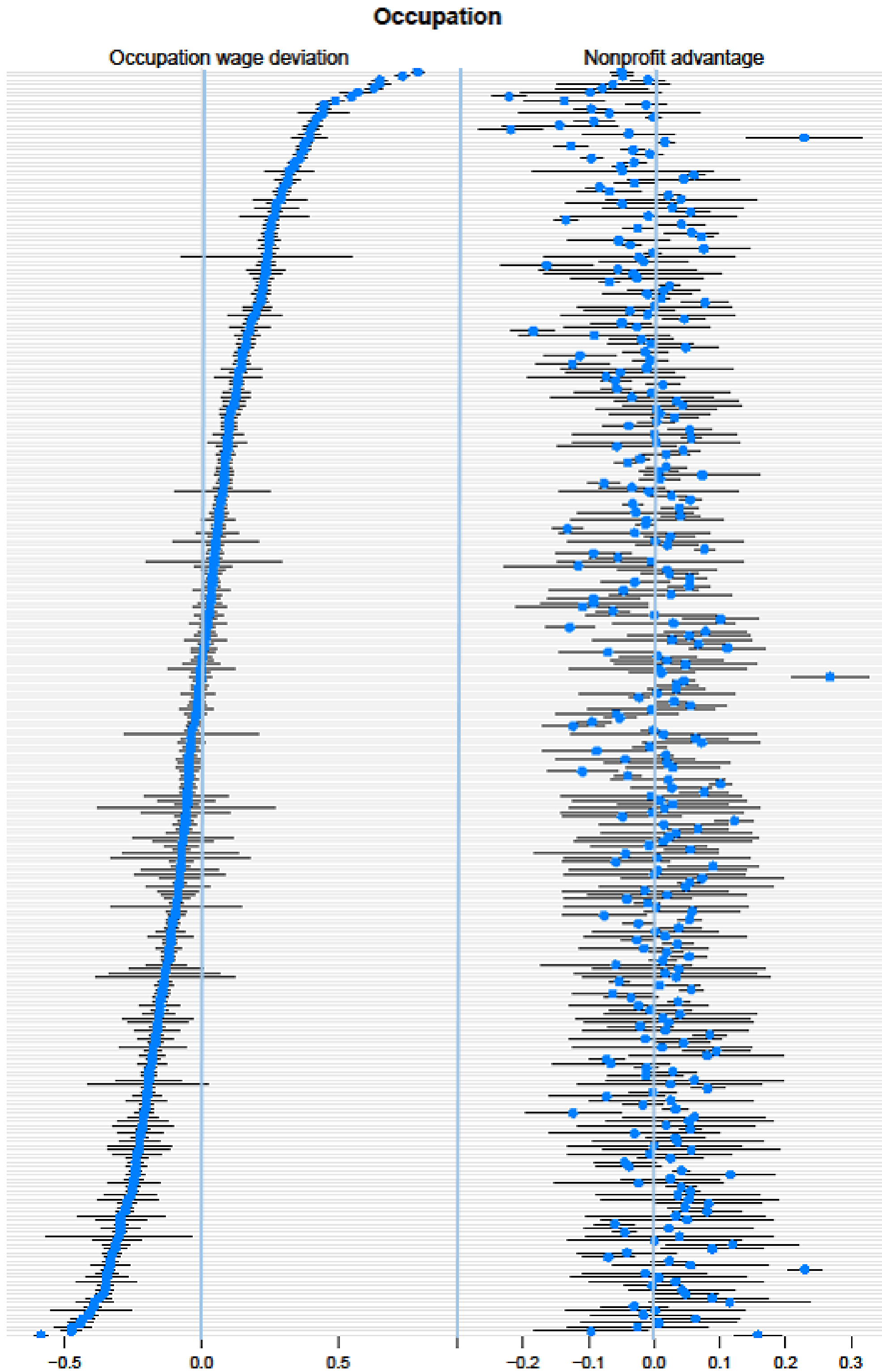



*Figure 15. Random effects of nonprofit pay differential on the occupation level*

Following musicians are bank tellers (383) and dentists (85) with 23 percent, taxi cab drivers and chauffeurs (809) with 16 percent, supervisors of cleaning and building (448) and ushers (502) with 12 percent occupation advantage for nonprofits. The five occupations with largest occupation pay disadvantages for nonprofits are lawyers (178) and financial services sales occupations (255) with 22 percent, actors, directors and producers (187) with 19 percent, business and promotion agents (34) with 17 percent, airplane pilots and navigators (226) with 14 percent less than for-profits. Taking lawyers as an example, adding their altruism motivation effect to the occupational disadvantage, nonprofit lawyers earn 28 percent less than for-profit lawyers, conditional on industry effects.

Occupation disadvantage for nonprofits does not necessarily mean it is a low-paying occupation. Due to the extensive list of occupations, I selected occupations at both ends (Table 14) to illustrate. Although lawyers (occupation code 178) have the extreme occupation disadvantage for nonprofits, the lawyer occupation is one of the highest-paying occupations. The lawyer occupation enjoys a pay of 55 percentage points above the grand mean, which is equivalent to 11.22 (=10.673+0.55) per year for a white male average for-profit lawyer, net of industry and state effects, and a comparable nonprofit lawyer is expected to earn 28 percent (-0.2231-0.057) less.

*Table 14. Nonprofit random effects on selected occupations*

| OCC1990 | Occupation title | Intercept | Nonprofit difference |
|---|---|---|---|
| 4 | Chief executives and public administrator | 0.7899 | -0.0495 |
| 34 | Business and promotion agents | 0.2353 | -0.1637 |
| 84 | Physicians | 0.7344 | -0.0480 |
| 85 | Dentists | 0.3956 | 0.2283 |
| 96 | Pharmacists | 0.6509 | -0.0089 |
| 87 | Optometrists | 0.6498 | -0.0628 |
| 66 | Actuaries | 0.6284 | -0.0789 |

| | | | |
|---|---|---|---|
| 88 | Podiatrists | 0.5718 | -0.0973 |
| 178 | Lawyers | 0.5477 | -0.2213 |
| 187 | Actors, directors, producers | 0.1759 | -0.1846 |
| 226 | Airplane pilots and navigators | 0.4076 | -0.1422 |
| 255 | Financial services sales occupations | 0.3987 | -0.2188 |
| 186 | Musician or composer | -0.0044 | 0.2678 |
| 383 | Bank tellers | -0.3397 | 0.2294 |
| 448 | Supervisors of cleaning and building service | -0.0574 | 0.1224 |
| 809 | Taxicab drivers and chauffeurs | -0.5859 | 0.1579 |

On the contrary, taxi cab drivers (809) enjoy a considerable occupation advantage for nonprofits, but it is the lowest-paying occupation. As an occupation, taxi drivers earn 59 percentage points below the average (constant) per year, net of industry and state effects. A nonprofit taxi driver earns 10.2 percent (0.1579-0.057) more than a comparable for-profit taxi cab driver. The highest-paying occupations include chief executives and public administrators (4), physicians (84), dentists (85), and pharmacists (96). It is common to see nonprofits to have occupation advantages in low-paying occupations and occupation disadvantages in high-paying occupations, although there are exceptions such as dentists.

***Nonprofit random effects inventory.***

The nonprofit wage differential varies across industries and occupations. Among all the nonprofit workers, although they all work for nonprofits, how much more they earn than comparable for-profit workers depends on the industry and the occupation they work for. The total nonprofit pay differential is the sum of donative labor effects and industry and occupation differences. Mathematically, it is reflected in the equation $\beta_{1(j1,j2,j3)} = \gamma_{1000} + r_{1(j1)} + r_{1(j2)}$. Random effects of the nonprofit pay differential are the residuals on industry and occupation levels of the nonprofit fixed coefficient, net of other effects such as gender, race, education, and state. Cross-classified multilevel modeling estimates the effect of industry and occupation separately without the confounding effect of the other, which means the modeling process produces an exhaustive inventory of nonprofit wage differentials. We can thus compute the nonprofit wage differential for each industry and occupation or each combination of industry and occupation. Appendices D and E provide detailed information.

I illustrate how it works using a coordinate system (Figure 16) with selected industries and occupations. Studies find that registered nurses are paid equally or slightly better in the nonprofit sector than in the for-profit. King and Lewis (2017) find a 3.9 percent premium for nonprofit registered nurses with all industries combined. Holtmann and Idson (1993) study the registered nurse in the nursing facility industry to find a 3 percent nonprofit advantage. The top three industries for registered nurses in the dissertation data are hospitals (6220), nursing facilities (6231), and insurance providers (5241). They make up 83% of the total registered nurse occupation. Locating in Figure 16, the industry advantages for these three industries are 0.102, 0.052, and 0.087, respectively, which means the final differences in pay for nonprofit registered nurses are 4 percent in hospitals, negative 1 percent for nursing care facilities, and 2.4 percent for insurance providers industries. These results include the -5.7 percent donative labor effects.

Managers in nonprofits get a pay lower than for-profit by 5 to 20 percent (Preston, 1989; Roomkin & Weisbrod, 1999). Figure (16) shows a 5 percent for a specific type of managers, CEOs and public administrators. The occupation disadvantage for nonprofits in addition to -5.7 percent donative labor effect, adding to a pay 10.7 percent lower than the for-profit managers. Lawyers earn 20% less (Weisbrod, 1983) or more than 40% less (Frank, 1996) in nonprofits than in for-profits. Figure (16) shows a negative 22 percent occupation wage difference for nonprofit lawyers in addition to -5.7 percent donative labor effect, which is close to 30 percent lower than comparable for-profit lawyers.

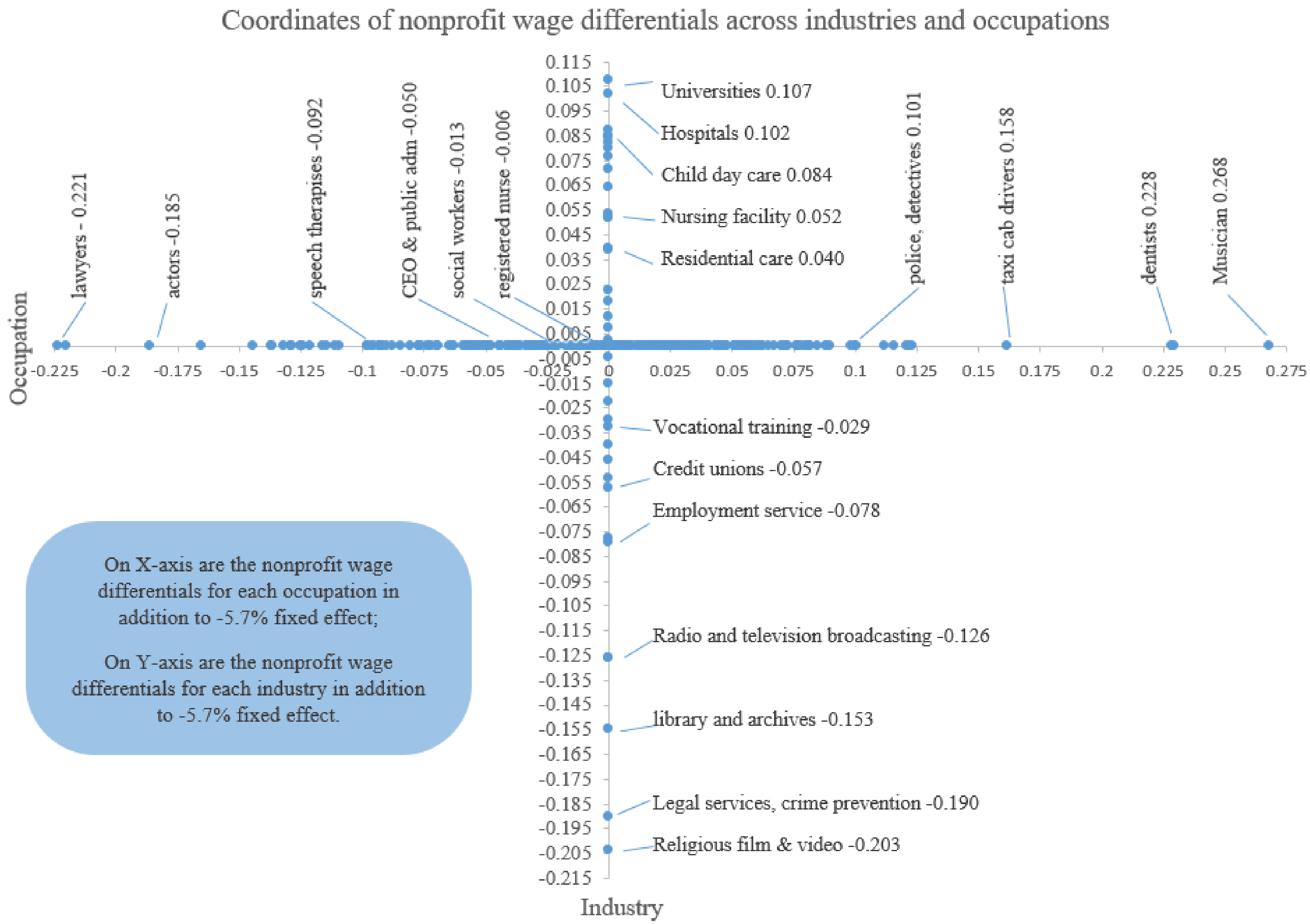



*Figure 16. Coordinates of nonprofit wage differential across industries and occupations*

In terms of industry, Preston (1988) finds a 0-10 percent nonprofit pay advantage in the daycare industry. In my dataset, under the child daycare industry, there are 151 occupation groups. Top three occupations: kindergarten and earlier school teachers, childcare workers, and managers in education and related field, make up 80 percent of the total employment under the childcare industry. The occupation differentials for the three occupations are 1.23, 3.35, and 2.29 percent, respectively. In the Figure, nonprofits have an 8.4 percent industry advantage. Adding to the donative labor effect, the nonprofit wage differentials for these three occupations in child daycare centers are 4 percent, 6 percent, and 5 percent, respectively.

The model analyzes the economy-wide data that include all industries and occupations and produces results consistent with previous research findings based on discrete industries or occupations. Therefore, the model reveals the complex structure of nonprofit wage differential, as well as provides a nuanced explanation of the seemingly contradictory and mixed findings in prevailing researches.

### 5.5 Hypotheses Testing: Measures 2-4 from SOI data

Commercialism has effects on pay and nonprofit pay differential because its focus on efficiency and cost minimization leads to changes in the work environment and behaviors of organizations. Measure 1, derived from frequencies of for-profit workers from the dataset, shows as a compositional effect. As a contrast, measures 2-4, the percentage of commercial revenue and percentage of program service revenue (Child, 2010; Foster & Bradach, 2005; Kerlin & Pollak, 2011), and inversed fundraising efforts are integral variables substantively describing the industry features.

These measures are computed solely based on IRS filing by nonprofit organizations. I only keep nonprofit workers in the dataset, yielding a sample with 664,646 observations in the same number of 308 occupations, 38 industries, and 51 states. Accordingly, I deleted the nonprofit variable. Therefore, there is no need to examine the random effects of the sectoral pay differential on the industry and occupation levels.

The unconditional model shows a slightly higher variability on the Level-2 than the full dataset. The industry level explains 7.4 percent of the total variance and occupation level explains 31 percent, compared with 7.3 percent by industry and 28 percent by occupation in the full dataset, respectively. The state-level variance remains less than 3 percent.

Table (15) is the descriptive statistics for centered variables (except for the dependent variable) in the nonprofit dataset. Commercial revenue and program service revenue make up more than 90 percent of the total revenue in these industries. Compared with them, the range of fundraising expense percentage is a lot smaller.

*Table 15. Summary for the nonprofit dataset (Total observations: 664,646)*

| VARIABLES | Mean | min | max | Std. Dev. |
|---|---|---|---|---|
| Natural log of annual income | 10.83 | 8.00 | 13.56 | 0.63 |
| Female percentage by occupation | 0.68 | 0.00 | 1.00 | 0.22 |
| Female | 0.68 | 0.00 | 1.00 | 0.46 |
| Years of education | 15.47 | 0.00 | 20.00 | 2.45 |
| Latino | 0.06 | 0.00 | 1.00 | 0.24 |
| White | 0.80 | 0.00 | 1.00 | 0.40 |
| Black | 0.08 | 0.00 | 1.00 | 0.27 |
| Asian | 0.05 | 0.00 | 1.00 | 0.21 |
| Other races | 0.02 | 0.00 | 1.00 | 0.14 |
| Manager | 0.16 | 0.00 | 1.00 | 0.36 |
| White-collar worker | 0.70 | 0.00 | 1.00 | 0.46 |
| Blue-collar worker | 0.14 | 0.00 | 1.00 | 0.35 |
| Work hours | 43.20 | 35.00 | 99.00 | 7.74 |
| Work experience | 22.74 | -5.00 | 59.00 | 11.70 |
| English speaking level (1-4) | 3.97 | 1.00 | 4.00 | 0.21 |
| Percentage of fundraising expense | 0.01 | 0.00 | 0.09 | 0.01 |
| Percentage of commercial revenue | 0.81 | 0.27 | 1.21 | 0.17 |
| Percentage of program service revenue | 0.76 | 0.01 | 0.94 | 0.20 |
| Volunteer total by industry (log) | 13.47 | 1.95 | 15.88 | 2.53 |
| Trend of fundraising expense percentage | 0.17 | -1.66 | 2.00 | 0.51 |

The correlation for all four measures (Table 4) shows that correlations of the dependent variable with the percentages of commercial revenue and program service revenue are very weak. Fundraising expense percentage measures the commitment of not engaging in a commercial approach. Despite its small range, it has a larger and negative relationship with annual income than the other two measures. Surprisingly, the natural log of volunteer total is positively related to the annual income of full-time nonprofit workers. All three measures are industry aggregate percentages from 2000 to 2012, and volunteer data are industry aggregate from 2008 to 2012 due to data availability.

I tested these measures with the full set of variables (Table 16). The results show that the percentages of commercial revenue and program service revenue are positive but not significant. The fundraising efforts measure is the total fundraising expense in 13 years, divided by total expense. To consider the potential trend of fundraising efforts, I generated a trend variable[34] in the models. The fundraising effort is negatively related to the outcome variable. As the percentage of fundraising expense increases by 1 percentage points, salary is estimated to reduce by 3 percent (Model S3). Considering the range of the measure is around 9 percentage points (Table 15), the difference in the highest and lowest industry pay is less than 30%. It shows that traditional nonprofits that rely on donative funding pay less than commercialized nonprofits that engage less in fundraising activities. The result aligns with my earlier argument that revenue percentages measure the results of commercialization, whereas fundraising efforts measure the intention to commercialize that determines organizations' subsequent behaviors. In the following models, I only used fundraising efforts as the key independent variable.

I also attach Model (9) in the full dataset in column 4 as a comparison. Female percentage by occupation reduces salary by 0.1 percent, but it is not significant in the full dataset. The effect of work hours is lower in the nonprofit sector than the full dataset. The return on education is 0.8 percentage points higher than the data for both sectors. The gender and racial equity are obvious in nonprofit workers. The gender pay gap is narrower by 6 percentage points

[34] $(fndrs\_eff_{2012} - fndrs\_eff_{2000})/(\frac{fndrs\_eff_{2000}+fndrs\_eff_{2012}}{2})$

than the full dataset. All racial groups have a smaller pay difference in pay than Whites, compared with the full data. The natural log of the volunteer total by industry is not significant in all models.

*Table 16. Test of measures and testing Hypothesis 2*

| | **Natural log of annual income** | | | |
|---|---|---|---|---|
| | **(S1)** | **(S2)** | **(S3)** | **(9)** |
| Percentage of commercial revenue | 0.001 | | | |
| | (1.318) | | | |
| Percentage of PSR | | 0.001 | | |
| | | (1.432) | | |
| Percentage of fundraising expense | | | -0.030*** | |
| | | | (-2.897) | |
| For-profit share of workers | | | | 0.003*** |
| | | | | (3.522) |
| Female percentage by occupation | -0.001** | -0.001** | -0.001** | -0.001 |
| | (-2.508) | (-2.508) | (-2.507) | (-1.451) |
| Volunteer total by industry (log) | -0.009 | -0.009 | -0.006 | |
| | (-1.425) | (-1.441) | (-0.920) | |
| Nonprofit | | | | -0.057*** |
| | | | | (-3.893) |
| Female | -0.133*** | -0.133*** | -0.133*** | -0.185*** |
| | (-105.864) | (-105.865) | (-105.866) | (-272.933) |
| Black | -0.044*** | -0.044*** | -0.044*** | -0.093*** |
| | (-22.340) | (-22.340) | (-22.344) | (-90.402) |
| Asian | -0.015*** | -0.015*** | -0.015*** | -0.029*** |
| | (-5.714) | (-5.714) | (-5.715) | (-21.799) |

| | | | | |
|---|---|---|---|---|
| Latino | -0.014*** | -0.014*** | -0.014*** | -0.063*** |
| | (-6.015) | (-6.015) | (-6.019) | (-57.061) |
| Other races | -0.036*** | -0.036*** | -0.036*** | -0.066*** |
| | (-9.500) | (-9.500) | (-9.501) | (-32.353) |
| Years of education | 0.081*** | 0.081*** | 0.081*** | 0.073*** |
| | (266.078) | (266.077) | (266.084) | (468.674) |
| Work experience | 0.010*** | 0.010*** | 0.010*** | 0.011*** |
| | (218.369) | (218.370) | (218.366) | (449.153) |
| Work experience squared | -0.048*** | -0.048*** | -0.048*** | -0.053*** |
| | (-125.040) | (-125.040) | (-125.039) | (-266.867) |
| Work hours per week | 0.008*** | 0.008*** | 0.008*** | 0.013*** |
| | (107.678) | (107.678) | (107.681) | (342.442) |
| Speak English | 0.052*** | 0.052*** | 0.052*** | 0.045*** |
| | (20.379) | (20.378) | (20.383) | (44.654) |
| Trend of fundraising percentage | | | 0.011 | |
| | | | (0.439) | |
| Constant | 10.671*** | 10.671*** | 10.671*** | 10.673*** |
| | (363.516) | (364.423) | (379.819) | (374.288) |
| **Random coefficients** | **No** | **No** | **No** | **Yes** |
| Observations | 664,646 | 664,646 | 664,646 | 3,017,110 |
| Akaike Inf. Crit. | 718,560 | 718,560 | 718,556 | 4,066,108 |
| Bayesian Inf. Crit. | 718,765 | 718,765 | 718,7723 | 4,066,393 |
| *Note:* | | | | *p**p***p<0.01 |

With no random coefficient, the models are simpler. I only used fundraising effort measure to test of Hypothesis 4 on manager-staff pay equity and Hypothesis 5 on gender pay equity (Table 17). Findings are consistent with the previous models. Managers earn 46 percent more than blue-collar workers (Model S4). Nonprofits engaging in more fundraising have a narrower occupation pay gap, which is not big but significant (Model S5). It shows that the choice of reliance on donative revenue or commercial revenue does have an impact on pay to nonprofit workers.

*Table 17. Modeling commercialism effects on the gender pay gap and manager-staff pay gap*

| | **Natural log of annual income** | | |
|---|---|---|---|
| | **(S4)** | **(S5)** | **(S6)** |
| Percentage of fundraising expense | -0.031*** | -0.028*** | -0.030*** |
| | (-2.906) | (-2.628) | (-2.877) |
| Manager | 0.233*** | 0.227*** | |
| | (3.800) | (3.694) | |
| Blue-collar worker | -0.223*** | -0.218*** | |
| | (-8.128) | (-7.925) | |
| Female percentage by occupation | -0.003*** | -0.003*** | -0.001** |
| | (-6.826) | (-6.777) | (-2.504) |
| Volunteer total by industry (log) | -0.006 | -0.006 | -0.006 |
| | (-0.916) | (-0.941) | (-0.917) |
| Female | -0.133*** | -0.133*** | -0.132*** |
| | (-105.878) | (-106.138) | (-100.535) |
| Black | -0.044*** | -0.044*** | -0.044*** |
| | (-22.333) | (-22.272) | (-22.321) |
| Asian | -0.015*** | -0.015*** | -0.015*** |
| | (-5.714) | (-5.711) | (-5.735) |
| Latino | -0.014*** | -0.014*** | -0.014*** |
| | (-6.017) | (-5.979) | (-6.038) |

| | | | |
|---|---|---|---|
| Other races | -0.036*** | -0.036*** | -0.036*** |
| | (-9.503) | (-9.474) | (-9.503) |
| Years of education | 0.081*** | 0.081*** | 0.081*** |
| | (265.943) | (266.137) | (265.946) |
| Work experience | 0.010*** | 0.010*** | 0.010*** |
| | (218.365) | (218.349) | (218.366) |
| Work experience squared | -0.048*** | -0.048*** | -0.048*** |
| | (-125.038) | (-125.065) | (-125.048) |
| Work hours per week | 0.008*** | 0.008*** | 0.008*** |
| | (107.666) | (107.734) | (107.717) |
| Trend of fundraising percentage | 0.011 | 0.011 | 0.011 |
| | (0.439) | (0.434) | (0.444) |
| Speak English | 0.052*** | 0.052*** | 0.052*** |
| | (20.364) | (20.279) | (20.391) |
| Percentage of fundraising expense × manager | | -0.014*** | |
| | | (-10.280) | |
| Percentage of fundraising expense × blue-collar | | 0.009*** | |
| | | (6.098) | |
| Percentage of fundraising expense × female | | | 0.003*** |
| | | | (3.058) |
| Constant | 10.738*** | 10.739*** | 10.671*** |
| | (382.194) | (381.256) | (379.968) |
| Observations | 664,646 | 664,646 | 664,646 |
| Akaike Inf. Crit. | 718,489 | 718,319 | 718,561 |
| Bayesian Inf. Crit. | 718,729 | 718,581 | 718,789 |
| *Note:* | | | *p**p***p<0.01 |

Model (S6) shows that in nonprofits that engage in less commercial approaches, the gender pay gap is narrower, although the size is not large. Therefore, both datasets show that either measured as the compositional effect or the contextual effect, commercialism increases pay and also increase pay gaps between genders and occupation types.

### 5.6 Sensitivity Analysis

To check the robustness and consistency of the estimates, I add different structures on Level-2 to compare the fixed effects of the nonprofit coefficient. Then, I use different subsets of the full data to run four selected models to check the consistency of the nonprofit coefficient.

***Different level-2 structures.***

In Table 18, Model (9) is the model I used for results in the dissertation. Model (T1) considers nonprofit wage differential also randomly varies on the state level in addition to industry and occupation levels. It reports a 4.7 percent negative nonprofit wage differential, reducing the size of nonprofit fixed effects by 1 percentage points.

Leete (2001) argues that nonprofit status, industry, occupation cannot be independently determined. Therefore, I created Model (T2) by adding an interaction term between industries and occupations as a control. It generates 38 industries, 308 occupations, 7,872 industry-occupation cells, and 51 states on Level-2.  In Model (T3), nonprofit is specified to vary across the interaction cells. The effects of the interaction cells are rather small, similar to Leete's (2001) conclusion. The coefficient for nonprofit remains to be robust to these changes. Even the strictest control still reports a 4.7 percent negative wage differential on average for nonprofit workers, net of industry and occupation variability.

*Table 18. Random slope coefficients on different levels*

| | Natural log of annual income | | | |
|---|---|---|---|---|
| **Fixed effects part** | **(9)** | **(T1)** | **(T2)** | **(T3)** |
| For-profit share of workers | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (3.537) | (3.554) | (3.887) | (3.979) |
| Female percentage by occupation | -0.001 | -0.001 | -0.0004 | -0.0003 |
| | (-1.445) | (-1.450) | (-0.906) | (-0.763) |
| Nonprofit | -0.057*** | -0.047*** | -0.050*** | -0.047*** |
| | (-3.893) | (-3.120) | (-3.950) | (-4.115) |
| Female | -0.185*** | -0.185*** | -0.182*** | -0.182*** |
| | (-272.933) | (-272.696) | (-268.881) | (-268.653) |
| Years of education | 0.073*** | 0.073*** | 0.070*** | 0.070*** |
| | (468.674) | (468.388) | (451.999) | (451.929) |
| Latino | -0.063*** | -0.064*** | -0.060*** | -0.060*** |
| | (-57.061) | (-57.446) | (-54.413) | (-54.396) |
| Black | -0.093*** | -0.093*** | -0.087*** | -0.087*** |
| | (-90.402) | (-90.831) | (-85.321) | (-85.175) |
| Asian | -0.029*** | -0.030*** | -0.029*** | -0.029*** |
| | (-21.799) | (-22.194) | (-21.597) | (-21.582) |
| Other races | -0.066*** | -0.066*** | -0.063*** | -0.063*** |
| | (-32.353) | (-32.550) | (-31.227) | (-31.190) |
| Speak English | 0.045*** | 0.046*** | 0.042*** | 0.042*** |
| | (44.654) | (45.161) | (41.934) | (41.815) |
| Work experience | 0.011*** | 0.011*** | 0.011*** | 0.011*** |
| | (449.153) | (449.266) | (448.990) | (449.056) |
| Work experience squared | -0.053*** | -0.053*** | -0.052*** | -0.052*** |
| | (-266.867) | (-266.927) | (-263.397) | (-263.339) |
| Work hours per week | 0.013*** | 0.013*** | 0.013*** | 0.013*** |

| | | | | |
|---|---|---|---|---|
| | (342.442) | (341.644) | (342.644) | (342.410) |
| Constant | 10.673*** | 10.673*** | 10.679*** | 10.680*** |
| | (374.288) | (374.238) | (393.187) | (394.085) |
| **Random effects part** | **Variance** | | | |
| Industry (Intercept) | 0.015718 | 0.015693 | 0.012761 | 0.012666 |
| Nonprofit | 0.006896 | 0.006829 | 0.005300 | 0.004288 |
| Occupation (Intercept) | 0.052737 | 0.052765 | 0.053803 | 0.053664 |
| Nonprofit | 0.005739 | 0.005789 | 0.003195 | 0.002041 |
| Industry×occupation (Intercept) | | | 0.011163 | 0.010701 |
| Nonprofit | | | | 0.003886 |
| State (intercept) | 0.011391 | 0.011431 | 0.011063 | 0.011054 |
| Nonprofit | | 0.000741 | | |
| Residual | 0.225067 | 0.224876 | 0.219502 | 0.219306 |
| Observations | 3,017,110 | 3,017,110 | 3,017,110 | 3,017,110 |
| Akaike Inf. Crit. | 4,066,108 | 4,063,689 | 3,998,534 | 3,996,937 |
| Bayesian Inf. Crit. | 4,066,393 | 4,063,999 | 3,998,831 | 3,997,260 |
| *Note:* | | | | *p**p***p<0.01 |

Beyond the small numeric difference, it is useful to think about the selection of coefficients for interpretation based on the purpose of the research. If the purpose is to predict, maybe Model (T3) should be selected because it controls more variability and yields more precision. However, Models (T2) and (T3) lack the theoretical foundation so far. With industry-occupation cells, the model aims to gauge the between-cell differences. In other words, Model (T3) cares about the difference in pay between any combinations of industry and occupation such as a social worker in the university industry and a subject instructor in the hospital industry, or the pay difference between a manager in a credit union and an artist in arts organizations. There is not enough theoretical or practical underpinning of why the examples mentioned above are important to study. Model (T1) can be a choice to examine how nonprofit pay differential varies across different states in addition to the random effects on industry and occupation levels if one's interest also includes the state level. In summary, Model (9) provides the estimates that are in line with current nonprofit theories given my purpose is to understand and explain the nonprofit pay differentials on industry and occupation levels.

***Different datasets.***

The first dataset is the full data without industries of hospital (6220) and higher education (6112). Table (19) shows that hospital industry (6220) makes up 16 percent of the sample, and higher education makes up another 4.12 percent. In total, they make up 20 percent of the total sample with different proportions of nonprofit and for-profit workers. These industries not only are large in size, but also occupy the higher end of industry wage differential: the nonprofit wage advantage over for-profit is 10.20 percent for hospitals, and 10.70 percent for higher education and universities (Appendix D).

*Table 19. Dropped industries for sensitivity analysis*

| Industry | | For-profit employees | | | Nonprofit employees | | |
|---|---|---|---|---|---|---|---|
| category | Total | Frequency | industry % | overall % | Frequency | industry % | overall % |
| 6112 | 124,307 | 48,165 | 38.75 | 1.60 | 76,142 | 61.25 | 2.52 |
| 6220 | 479,007 | 252,313 | 52.56 | 8.36 | 226,694 | 47.33 | 7.51 |
| Total | 603,314 | 300,478 | | 9.96 | 302,836 | | 10.03 |

The second dataset is the one-year data Census 2000 with a sample size of 649,227, which is 21.52 percent of the dataset used in the dissertation. The third dataset is the same dataset, but with the original 58 industry categories from ACS without combining into 38 categories. The major difference between the 38 industries and 58 industries lies in "public utilities" where six categories are combined into one, and "transportation" where nine categories ranging from air transportation, truck transportation to pipeline transportation and services incidental to transportation are combined into one category (Appendix B).

Table (20) shows how variance components change across different datasets. Whether having the "outlier" industries does not seem to affect the variance components, but having more industry categories increases the variance on the industry level.

*Table 20. Comparing variance components (IUCC)*

| | **The proportion of variance on each level** | | | |
|---|---|---|---|---|
| | **38 industries** | **No hospital and higher education** | **Census 2000** | **58 industries** |
| Industry | [7.3%] | [7.16%] | [6.81%] | [10.5%] |
| Occupation | [28%] | [27.64%] | [25.00%] | [26.1%] |
| State | [2.8%] | [2.82%] | [3.25%] | [2.6%] |
| Residual | 0.28486 | 0.29838 | 0.26634 | 0.28052 |
| Constant | $10.589^{***}$ | $10.592^{***}$ | $10.584^{***}$ | $10.642^{***}$ |
| | (269.161) | (260.576) | (287.944) | (277.167) |
| Observations | 3,017,110 | 2,423,796 | 649,227 | 3,017,110 |
| Akaike Inf. Crit. | 4,776,157 | 3,933,485 | 985,622 | 4,729,958 |
| Bayesian Inf. Crit. | 4,776,222 | 3,933,548 | 985,679 | 4,730,022 |

Next, I compared random intercept models (Table 21). Assuming that the nonprofit wage differential does not vary across industries and occupations, the commercialism effect remains similar, and the nonprofit pay differential is under 1 percent except for the dataset without hospitals and higher education. Without hospitals and universities, even though we assume nonprofit pay differential is the same across the rest 36 industries, nonprofit workers earn 3 percent less than the for-profit workers. It reflects the overwhelming impact of these two industries on the economy-wide nonprofit wage differential estimate due to their large industry sizes and industry pay advantages for nonprofits.

*Table 21. Comparing models with no random slopes*

| | Natural log of annual income | | | | | |
|---|---|---|---|---|---|---|
| | **38 industries** | **No hospital and higher education** | **Census 2000** | **58 industries (full-time worker)** | **58 industries (including part-time worker)** | **289 industries (full-time worker)** |
| For-profit share of workers | 0.004*** | 0.004*** | 0.003*** | 0.004*** | 0.005*** | 0.003*** |
| | (4.213) | (4.035) | (4.493) | (4.505) | (4.944) | (4.970) |
| Female percentage by occupation | -0.001 | -0.001 | -0.001*** | -0.001 | -0.001 | -0.00001 |
| | (-1.521) | (-1.300) | (-2.812) | (-1.161) | (-1.298) | (-0.026) |
| Nonprofit | 0.002*** | -0.030*** | -0.008*** | 0.007*** | 0.010*** | -0.001 |
| | (2.891) | (-28.381) | (-4.649) | (9.188) | (13.139) | (-0.958) |
| Female | -0.187*** | -0.197*** | -0.199*** | -0.184*** | -0.158*** | -0.193*** |
| | (-276.068) | (-254.826) | (-138.037) | (-271.682) | (-236.715) | (-463.042) |
| Years of education | 0.073*** | 0.072*** | 0.072*** | 0.072*** | 0.068*** | 0.062*** |
| | (469.262) | (411.452) | (216.209) | (464.580) | (461.408) | (714.735) |
| Latino | -0.065*** | -0.073*** | -0.049*** | -0.072*** | -0.035*** | -0.053*** |
| | (-58.414) | (-58.487) | (-18.974) | (-67.001) | (-28.958) | (-72.420) |
| Black | -0.095*** | -0.104*** | -0.059*** | -0.093*** | -0.062*** | -0.103*** |
| | (-92.220) | (-88.045) | (-27.331) | (-91.134) | (-61.282) | (-151.374) |
| Asian | -0.030*** | -0.035*** | -0.034*** | -0.039*** | -0.005*** | -0.016*** |
| | (-22.173) | (-21.640) | (-10.345) | (-29.690) | (-3.318) | (-17.770) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Other races | -0.067*** | -0.071*** | -0.071*** | -0.067*** | -0.059*** | -0.072*** |
| | (-32.827) | (-30.747) | (-16.862) | (-33.299) | (-30.718) | (-57.598) |
| Speak English | 0.046*** | 0.045*** | 0.045*** | 0.037*** | 0.020*** | 0.051*** |
| | (44.993) | (40.148) | (19.443) | (18.206) | (24.324) | (109.259) |
| Work experience | 0.011*** | 0.011*** | 0.012*** | 0.011*** | 0.013*** | 0.010*** |
| | (448.690) | (380.215) | (212.464) | (439.095) | (548.223) | (690.076) |
| Work experience squared | -0.053*** | -0.052*** | -0.052*** | -0.053*** | -0.061*** | -0.052*** |
| | (-267.026) | (-229.762) | (-115.216) | (-268.668) | (-331.493) | (-444.157) |
| Work hours per week | 0.013*** | 0.015*** | 0.012*** | 0.013*** | 0.877***[35] | 0.015*** |
| | (345.041) | (342.001) | (156.982) | (333.049) | (1,132.333) | (643.305) |
| Work weeks per year | | | | | 0.241*** | |
| | | | | | (1,006.384) | |
| Constant | 10.682*** | 10.679*** | 10.660*** | 10.728*** | 10.415*** | 10.736*** |
| | (368.283) | (362.015) | (400.583) | (373.906) | (354.715) | (519.903) |
| **Random coefficients** | **No** | **No** | **No** | **No** | **No** | **No** |
| Observations | 3,017,110 | 2,413,796 | 649,227 | 3,017,110 | 4,306,670 | 8,131,265 |
| Akaike Inf. Crit. | 4,078,169 | 3,366,409 | 839,050 | 4,049,456 | 7,122,774 | 10,649,186 |
| Bayesian Inf. Crit. | 4,078,401 | 3,366,638 | 839,254 | 4,049,689 | 7,123,026 | 10,649,436 |
| *Note:* | | | | | | *p**p***p<0.01 |

[35] "Work hours per week" variable in this model is log form in this model because this dataset includes part-time workers.

Models in Table (22) are different from Table (21) by specifying random coefficients for nonprofit on industry and occupation levels. With the random effects of nonprofits, coefficients for commercialism and nonprofit are highly consistent across different datasets. The large-size industry outliers do not seem to matter much because the variability on Level-2 (including industry level) is removed. Despite the consistency, there is a noticeable difference in the nonprofit coefficient between dataset with 58 categories and 38 categories.

*Table 22. Comparing random slope models on different datasets*

| | Natural log of annual income | | | | | |
|---|---|---|---|---|---|---|
| | **38 industries** | **No hospital and higher education** | **Census 2000** | **58 industries (full-time workers** | **58 industries (including part-time workers)** | **289 industries (full-time workers)** |
| For-profit share of workers | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.004*** | 0.002*** |
| | (3.537) | (3.704) | (4.032) | (3.966) | (4.516) | (3.650) |
| Female percentage by occupation | -0.001 | -0.001 | -0.001** | -0.001 | -0.001 | -0.0001 |
| | (-1.445) | (-1.193) | (-2.502) | (-1.237) | (-1.391) | (-0.333) |
| Nonprofit | -0.057*** | -0.052*** | -0.052*** | -0.043*** | -0.061*** | -0.069*** |
| | (-3.893) | (-3.740) | (-3.232) | (-3.734) | (-5.075) | (-10.712) |
| Female | -0.185*** | -0.195*** | -0.197*** | -0.182*** | -0.157*** | -0.191*** |
| | (-272.933) | (-252.379) | (-136.445) | (-268.797) | (-234.088) | (-460.075) |
| Years of education | 0.073*** | 0.072*** | 0.072*** | 0.072*** | 0.068*** | 0.062*** |
| | (468.674) | (411.713) | (215.958) | (464.257) | (460.124) | (713.869) |
| Latino | -0.063*** | -0.072*** | -0.048*** | -0.071*** | -0.034*** | -0.052*** |
| | (-57.061) | (-57.638) | (-18.383) | (-65.443) | (-28.086) | (-71.475) |
| Black | -0.093*** | -0.103*** | -0.057*** | -0.091*** | -0.060*** | -0.101*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-90.402) | (-87.243) | (-26.225) | (-89.215) | (-59.519) | (-149.700) |
| Asian | -0.029*** | -0.035*** | -0.033*** | -0.039*** | -0.004*** | -0.015*** |
| | (-21.799) | (-21.575) | (-10.135) | (-29.216) | (-3.007) | (-17.215) |
| Other races | -0.066*** | -0.070*** | -0.070*** | -0.066*** | -0.058*** | -0.072*** |
| | (-32.353) | (-30.469) | (-16.557) | (-32.785) | (-30.263) | (-57.189) |
| Speak English | 0.045*** | 0.044*** | 0.045*** | 0.037*** | 0.020*** | 0.051*** |
| | (44.654) | (39.168) | (19.234) | (18.168) | (24.131) | (109.008) |
| Work experience | 0.011*** | 0.011*** | 0.012*** | 0.011*** | 0.013*** | 0.010*** |
| | (449.153) | (380.659) | (213.024) | (439.536) | (547.803) | (689.900) |
| Work experience squared | -0.053*** | -0.052*** | -0.052*** | -0.053*** | -0.060*** | -0.052*** |
| | (-266.867) | (-229.639) | (-115.305) | (-268.437) | (-330.790) | (-443.701) |
| Work hours per week | 0.013*** | 0.015*** | 0.012*** | 0.013*** | 0.874*** | 0.015*** |
| | (342.442) | (342.092) | (155.657) | (330.879) | (1,127.351) | (642.373) |
| Work weeks per year | | | | | 0.241*** | |
| | | | | | (1,007.241) | |
| Constant | 10.673*** | 10.674*** | 10.654*** | 10.722*** | 10.408*** | 10.734*** |
| | (374.288) | (365.038) | (409.194) | (376.069) | (356.224) | (518.523) |

| Random coefficients | Yes | Yes | Yes | Yes | Yes | Yes |
|---|---|---|---|---|---|---|
| Observations | 3,017,110 | 2,413,796 | 649,227 | 3,017,110 | 4,306,670 | 8,131,265 |
| Akaike Inf. Crit. | 4,066,108 | 3,358,306 | 836,488 | 4,038,292 | 7,110,175 | 10,632,677 |
| Bayesian Inf. Crit. | 4,066,393 | 3,358,586 | 836,739 | 4,038,576 | 7,110,481 | 10,632,983 |

*Note:* $^{*}p^{**}p^{***}p<0.01$

The following table shows that the average salary for “transportation” in original categories varies with a wide range of 10.25 ($28,283) and 11.26 ($77,653). “Truck transportation” makes up 45 percent of the large category. The more categories, the more between-group variance is captured on Level-2. Thus, there should be comparatively less difference (more accuracy) on Level-1 estimates.

| Industry in 58 categories | Mean of income | Frequencies | In 38 categories | Mean of income | Frequencies |
|---|---|---|---|---|---|
| 481 Air transportation | 10.96651 | 44,360 | | | |
| 482 Rail transportation | 11.10162 | 25,362 | | | |
| 483 Water transportation | 11.03975 | 4,777 | | | |
| 484 Truck transportation | 10.73268 | 120,687 | | | |
| 4853 Taxi and limousine service | 10.25499 | 6,428 | 4800 | 10.80458 | 267,260 |
| 485M Bus service and urban transit | 10.56718 | 16,309 | | | |
| 486 Pipeline transportation | 11.25552 | 5,248 | | | |
| 487 Scenic and sightseeing transportation | 10.59979 | 1,515 | | | |
| 488 Services incidental to transportation | 10.76195 | 42,574 | | | |

On the one hand, this is the condition when I need to merge ACS data to SOI data because SOI has only one category of “transportation.” On the other hand, the theoretical argument on the measurability of service quality, efficiency, and commercialism prefers combined 38 industry categories to the 58 categories. No matter it is air transportation, rail transportation, or taxi services, they are not different in terms of the potential to commercialize. In other words, the 38-category model presents the results that are better explained by theories.

I have restricted the analysis to full-time workers based on the consideration of motivation sorting. Other studies, such as Ruhm and Borkoski (2003), suggest that the nonprofit sector has more part-time workers. Hirsch (2005) find that part-time workers often have compensation penalty because of interruption of tenure and work experience. Hence, including part-time workers in the study might strengthen the negative nonprofit wage differential, which, however, may not necessarily relate to the donative labor effect. My analysis of the dataset that includes part-time workers shows that, controlling for work hours per week and work weeks per year, nonprofit workers earn 6.1 percent less than comparable for-profit workers (Table 22).

The dissertation data only kept 58 industries. I also did a supplementary analysis using the full list of 289 industries in the ACS (with the same model) estimates a negative 7 percent nonprofit wage differential (Table 22).

Table (23) compares commercialism effect on the manager-staff pay gap in the two sectors. Coefficients for constituent variables of commercialism, nonprofit, managers, and blue-collar worker are similar across different datasets. However, interaction effects are different. In the dataset with 58 industries, commercialism is not significant. The sectoral difference in occupation types is only significant in Census 2000 at a 10 percent level. The three-way interaction effects are significant in three large datasets at a 1 percent level and only significant at a 10% level in Census 2000. Therefore, cautions are needed in interpreting the three-way interaction effects on occupation types.

*Table 23. Testing manager-staff pay gap across different datasets*

| | **Natural log of annual income** | | | |
|---|---|---|---|---|
| | **38 industries** | **No hospital and higher education** | **Census 2000** | **58 industries** |
| For-profit share of workers | $0.003^{***}$ | $0.003^{***}$ | $0.003^{***}$ | $0.004^{***}$ |
| | (3.951) | (4.026) | (4.506) | (4.146) |

| | | | | |
|---|---|---|---|---|
| Nonprofit | -0.058*** | -0.046*** | -0.056*** | -0.046*** |
| | (-4.254) | (-4.142) | (-3.661) | (-4.059) |
| Manager | 0.223*** | 0.211*** | 0.201*** | 0.229*** |
| | (3.676) | (3.377) | (3.805) | (3.903) |
| Blue-collar worker | -0.244*** | -0.251*** | -0.185*** | -0.254*** |
| | (-9.480) | (-9.469) | (-8.050) | (-10.203) |
| For-profit share of workers × nonprofit | -0.001** | -0.001* | -0.001** | -0.001 |
| | (-2.276) | (-1.933) | (-2.120) | (1.431) |
| For-profit share of workers × manager | -0.0005*** | -0.0003*** | -0.0004*** | 0.0001 |
| | (-7.217) | (-3.697) | (-3.124) | (1.091) |
| Nonprofit × manager | -0.017 | -0.030 | -0.041* | -0.015 |
| | (-0.695) | (-1.155) | (-1.779) | (-0.646) |
| For-profit share of workers × blue-collar | -0.0003*** | 0.0001 | -0.0003*** | -0.0001** |
| | (-5.685) | (0.784) | (-3.403) | (-2.432) |
| Nonprofit × blue-collar | 0.011 | 0.017 | 0.022* | 0.019* |
| | (0.977) | (1.434) | (1.735) | (1.722) |
| For-profit share of workers × nonprofit × manager | -0.0003** | 0.001*** | -0.0005* | -0.001*** |
| | (-2.317) | (5.373) | (-1.901) | (-4.517) |
| For-profit share of workers × nonprofit × blue-collar | 0.001*** | -0.001*** | 0.0004* | 0.001*** |
| | (5.223) | (-3.676) | (1.907) | (4.562) |
| Female | -0.185*** | -0.195*** | -0.197*** | -0.182*** |
| | (-272.826) | (-252.407) | (-136.405) | (-268.708) |
| Female percentage by occupation | -0.003*** | -0.003*** | -0.002*** | -0.003*** |
| | (-6.368) | (-6.046) | (-6.542) | (-6.476) |
| Years of education | 0.073*** | 0.072*** | 0.072*** | 0.072*** |
| | (468.362) | (411.464) | (215.609) | (464.138) |

| | | | | |
|---|---|---|---|---|
| Latino | -0.063*** | -0.072*** | -0.048*** | -0.071*** |
| | (-56.996) | (-57.616) | (-18.346) | (-65.383) |
| Black | -0.093*** | -0.103*** | -0.057*** | -0.091*** |
| | (-90.374) | (-87.228) | (-26.207) | (-89.190) |
| Asian | -0.029*** | -0.035*** | -0.033*** | -0.039*** |
| | (-21.808) | (-21.563) | (-10.131) | (-29.214) |
| Other races | -0.066*** | -0.070*** | -0.070*** | -0.066*** |
| | (-32.352) | (-30.463) | (-16.555) | (-32.790) |
| Speak English | 0.045*** | 0.044*** | 0.045*** | 0.037*** |
| | (44.445) | (39.163) | (19.120) | (18.005) |
| Work experience | 0.011*** | 0.011*** | 0.012*** | 0.011*** |
| | (448.933) | (380.598) | (212.958) | (439.413) |
| Work experience squared | -0.053*** | -0.052*** | -0.052*** | -0.053*** |
| | (-266.876) | (-229.640) | (-115.321) | (-268.448) |
| Work hours per week | 0.013*** | 0.015*** | 0.012*** | 0.013*** |
| | (342.449) | (342.098) | (155.644) | (330.865) |
| Constant | 10.726*** | 10.727*** | 10.701*** | 10.776*** |
| | (382.584) | (372.267) | (414.492) | (385.577) |
| **Random coefficients** | **Yes** | **Yes** | **Yes** | **Yes** |
| Observations | 3,017,110 | 2,413,796 | 649,227 | 3,017,110 |
| Akaike Inf. Crit. | 4,065,990 | 3,358,287 | 836,482 | 4,038,238 |
| Bayesian Inf. Crit. | 4,066,390 | 3,358,680 | 836,835 | 4,038,638 |
| *Note:* | | | | *p**p***p<0.01 |

The last comparison is the commercialism effect on the gender pay gap between the two sectors (Table 24). Both commercialism and nonprofit have significant moderating effects on the gender pay gap. Three-way interaction terms are highly consistent across different datasets, showing greater gender pay equity in the nonprofit sector and enlarging sector gap of gender pay due to commercialism.

*Table 24. Testing the gender pay gap across different datasets*

| | Natural log of annual income | | | |
|---|---|---|---|---|
| | **38 industries** | **No hospital and higher education** | **Census 2000** | **58 industries** |
| For-profit share of workers | 0.003*** | 0.004*** | 0.003*** | 0.004*** |
| | (4.028) | (4.127) | (4.569) | (4.302) |
| Nonprofit | -0.051*** | -0.047*** | -0.048*** | -0.038*** |
| | (-3.687) | (-3.545) | (-3.162) | (-3.368) |
| Female | -0.173*** | -0.175*** | -0.183*** | -0.181*** |
| | (-214.237) | (-176.423) | (-102.772) | (-227.388) |
| For-profit share of workers × nonprofit | -0.001** | -0.001* | -0.001** | -0.001 |
| | (-2.391) | (-1.798) | (-2.155) | (-1.552) |
| For-profit share of workers × female | -0.002*** | -0.002*** | -0.001*** | -0.002*** |
| | (-51.135) | (-35.196) | (-18.041) | (-46.462) |
| Nonprofit × female | 0.039*** | 0.048*** | 0.047*** | 0.040*** |
| | (18.376) | (18.996) | (10.138) | (16.638) |
| For-profit share of workers × nonprofit × female | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (16.166) | (10.177) | (6.110) | (12.500) |
| Female percentage by occupation | -0.001** | -0.001** | -0.001*** | -0.001* |
| | (-2.129) | (-2.165) | (-3.391) | (-1.702) |
| Years of education | 0.073*** | 0.072*** | 0.072*** | 0.072*** |
| | (466.470) | (410.258) | (215.241) | (462.354) |

| | | | | |
|---|---|---|---|---|
| Latino | -0.063*** | -0.072*** | -0.048*** | -0.071*** |
| | (-57.234) | (-57.869) | (-18.468) | (-65.640) |
| Black | -0.092*** | -0.102*** | -0.056*** | -0.091*** |
| | (-89.762) | (-86.628) | (-25.994) | (-88.629) |
| Asian | -0.028*** | -0.034*** | -0.033*** | -0.038*** |
| | (-21.142) | (-21.297) | (-9.941) | (-28.678) |
| Other races | -0.065*** | -0.070*** | -0.070*** | -0.066*** |
| | (-32.095) | (-30.332) | (-16.462) | (-32.546) |
| Speak English | 0.046*** | 0.044*** | 0.045*** | 0.038*** |
| | (44.952) | (39.365) | (19.331) | (18.376) |
| Work experience | 0.011*** | 0.011*** | 0.012*** | 0.011*** |
| | (449.442) | (380.881) | (212.861) | (439.710) |
| Work experience squared | -0.053*** | -0.052*** | -0.052*** | -0.053*** |
| | (-267.573) | (-230.087) | (-115.670) | (-269.027) |
| Work hours per week | 0.013*** | 0.015*** | 0.012*** | 0.013*** |
| | (341.448) | (341.474) | (155.232) | (330.112) |
| Constant | 10.670*** | 10.671*** | 10.651*** | 10.718*** |
| | (374.942) | (364.642) | (409.888) | (377.678) |
| **Random coefficients** | **Yes** | **Yes** | **Yes** | **Yes** |
| Observations | 3,017,110 | 2,413,796 | 649,227 | 3,017,110 |
| Akaike Inf. Crit. | 4,061,180 | 3,355,506 | 835,707 | 4,034,256 |
| Bayesian Inf. Crit. | 4,061,516 | 3,355,836 | 836,003 | 4,034,592 |
| *Note:* | | | | *p**p***p<0.01 |

To summarize the sensitivity tests, as long as the models include random coefficients of nonprofit on industry and occupation levels, the estimates are robust. Even if including the random effects on the incomprehensible level, there is a significant 4.7 percentage negative nonprofit wage differential on average. Across different datasets, minor disparities occur between the 38 industries and 58 industries.

# Chapter VI. Discussions and Conclusion

To answer the theoretical questions about whether altruistically motivated workers donate their labor to nonprofits and what is the effect of commercialism, I have analyzed cross-sectional data pooled from 12 years of American Community Survey and Census 2000. Donative labor effect has been assessed through multi-level random effects modeling. The effect of commercialism has been assessed through different measures. Then, I have run a series of sensitivity analyses to check the consistency of the results. In this chapter, I recapitulate the main finding, building on which I discuss the implications, contributions, and limitations of the research.

## Summary of findings

Whether nonprofit workers earn more than for-profit workers has been an unsettled question for long. Findings of negative nonprofit pay differentials (Handy et al., 2007; Preston, 1990a; Weisbrod, 1983) have been continuously compromised by counter-findings (Holtmann & Idson, 1993; King & Lewis, 2017; Preston, 1988) or findings of equal pay (Ben-Ner et al., 2011; Hirsch et al., 2018; Leete, 2001). In the meantime, multiple industry and economy-wide studies acknowledge significantly positive or negative differentials in some industries.

These studies have laid a great foundation and also made a strong appeal for further inquiry on the disagreement of findings. Results of discrete industries or occupations cannot be inferred to other industries or occupations because the research findings are contradictory. The assumption in economy-wide studies that nonprofit pay differential is the same across industries and occupations leads to a confounded estimate that there is no donative labor effect. My dissertation addresses these conflicts by asking what is the fixed coefficient of nonprofit wage differential that is global to all nonprofit workers and what is the random effect that is local to different groups: industries and occupations. Put it another way, I examine the nonprofit wage differential as a composite of nonprofit effect, industry effect, and occupation effect.

The reframing of nonprofit wage differential as a composite is grounded in theories that explain phenomena on different levels, namely, donative labor theory on the individual level, attenuated property rights theory on the organizational level, and efficiency wage theory on the firm or industry level. I deconstructed the theory on their background, empirical evidence, and levels of explanation. Based on the explanatory level of theories, I developed my hypotheses and tested them using CCREM.

**The meaning of random effects.**

Comparing Model (7) with only Level-1 variables and Model 8 with all variables suggests that commercialism reduces the industry wage dispersion by 5 percentage points. The inter-industry wage differentials, or the rank of industry pay (left panel of Figure 14), is important when we consider pay equity. Holding constant all variables, Level-1 errors, occupation and state effects in the model, the dispersion of industry-level pay is between -0.26 and 0.30 around the mean (10.73). The random slope model (Model 9) shows that random intercepts are negatively correlated with the nonprofit random slopes on the industry level, meaning that industries where nonprofits pay more than the for-profits are usually low-pay industries. For instance, several frequently studied industries with positive nonprofit wage differentials, such as day-care centers, residential care facilities, nursing facilities, are among the lowest-paying industries below the average (Figure 14). In many other higher-pay industries such as rehabilitation centers and libraries, nonprofits have large negative pay differentials.

**Effects of commercialism.**

Industries are the contexts that have different attributes such as competition level, entry and funding requirement, commercialism, types of services, and revenue sources. All of these can affect the organization actors in the industry. The dissertation examines the effects of commercialism. Either measured as the for-profit share of workers or inverse of fundraising efforts, commercialism increases pay because of its potential focus on efficiency and cost minimization, which triggers the compensating wage mechanism.  Commercialism intervenes the nonprofit wage differential through changing behaviors of organizations that strive to commercialize.  As explained by compensating wage theory, less pleasant working conditions invoke higher pay. The effects of fundraising efforts on decreasing pay (for only nonprofit worker dataset) appear to be stronger than the effects of the for-profit share of workers (for all full-time workers).

The compensating wage mechanism is further confirmed in models with the moderating effect of commercialism. The nonprofit sector is reputed to have more pay equity in the gender pay difference and the manager-staff pay difference. Commercialism moderates the pay equity as well as the sector pay differential. The pay gap between nonprofits and for-profits is larger in more commercialized industries than less commercialized ones. In more commercialized industries, the gender pay gap and manager-staff pay gap are wider.

**Effects of donative labor.**

Nonprofit organizations generally serve the public interest and social missions. Thus, nonprofits often attract altruistically motivated workers who are willing to sacrifice personal benefits to produce positive social externalities. On average, the effect of donative labor is that nonprofit workers earn 5.7 percent less than comparable for-profit workers controlling for industry, occupation, and state effects. Sensitivity tests show that it is between negative 4.7 percent and negative 5.7 percent.

**Implications**

**Donative labor under the mask**. The inability to test theories has practical and policy implications. Contradictory or divergent results generate uncertainty, doubt, questioning on nonprofits as a sector. Confounding industry and occupation contexts make nonprofits "for-profits in disguise" (Holtmann & Idson, 1993; Roomkin & Weisbrod, 1999; Weisbrod, 1988), leading to the illusion that altruism does not exist and nonprofit workers do not donate their labor to nonprofits (Ruhm & Borkoski, 2003), which compromises the legitimacy of the nonprofit sector.

My findings reveal that altruism and motivation sorting lead to lower pay for nonprofit workers than comparable for-profit workers. It is part of the total nonprofit wage differential in addition to the effects on industry and occupation levels. Decomposing sources of effects suggest that, instead of asking why there is an inconsistency of the sectoral pay differential, we should ask why there is an industry or occupation difference. Asking the right question could restore the legitimacy of nonprofit to their constituents, including clients, policymakers, and other stakeholders, as well as developing more insightful research directions.

**Commercialism hurts under the mask**. Salamon (1993, 1999, 2015) argue that, facing "fiscal squeeze" of government budget and "economic crisis" of competing with the for-profit firms to serve similar clients, nonprofits not only develop resilience to sustains the growth of the sector through commercialization, but also suffers from erosion of values that nonprofits hold dear such as democracy and citizenship (Eikenberry & Kluver, 2004). In the case of pay differential, commercialism increases the pay to both for-profit and nonprofit workers because the deprivation of pleasant working conditions as a result of efficiency pursuit gets compensated as a monetary reward. However, commercialism does not increase the pay equally. It increases pay more for men and managers in the for-profit sector, leading to a widening horizontal sectoral pay gap for employees with the same job and a widening vertical wage dispersion and inequality for employees on different occupation types (Gupta, Conroy, & Delery, 2012). Wage dispersion and inequality might affect employee satisfaction (Pfeffer & Langton, 1993), service quality, and work efforts (Hamann & Ren, 2013).

**Rethinking efficiency**. Organizations with high efficiency can achieve more with the same resources. Therefore, efficiency is desired in many areas, such as operational efficiency, financial efficiency, and programmatic efficiency (Callen, Klein, & Tinkelman, 2003; Eikenberry & Kluver, 2004; Frumkin & Andre-Clark, 2000). On the contrary, inefficiency is a word with negative connotation under the prevalent commercialized discourse, and "inefficient" nonprofits might be perceived as inferior to "efficient" organizations. To commercialize and adopt a business mindset might improve the image of the organization of being more efficient as well as bring some immediate benefits. However, commercialism might work as a double-edged sword for nonprofits to lose their visions and values. Frumkin and Andre-Clark (2000) argue that the value-driven approach is the competitive edge for nonprofits to sustain better outcomes, rather than a superficial imitation of efficiency strategies. In the overwhelming commercialism context, it is useful to be aware of the unanticipated consequence of the behaviors of the organization. After all, nonprofit survive "*not despite* but *because of* their notorious lack of efficiency" (Seibel, 2013, p. 107) due to their special social functions between the market and the government.

## Contributions

In the dissertation, I have analyzed economy-wide data to examine the nature and magnitude of nonprofit wage differential relative to the for-profit sector. Building on existing studies, I have contributed to re-conceptualizing the issue under the multilevel theoretical and analytical framework, providing nationally representative and exhaustive estimates of the nonprofit pay differential, and establishing empirical linkage of commercialism to pay in the nonprofit sector.

Multilevel conceptualization of the nonprofit pay is rooted in different explanatory levels of theories relevant to the nonprofit pay. Donative wage theory is about one specific nature, tendency, or trait owned by individuals: altruism motivation. On the organizational level, theory differentiates nonprofit organizations by the tax-exempt status and non-distribution constraints, which is related to attenuated property rights. On the industry level, industries dominated by for-profits gravitate more on profit and efficiency, whereas industries dominated by nonprofits lean more towards social capital building and inefficiency. Therefore, nonprofit wage differential can be examined from the individual level, organizational level, and industry level. In the dissertation, constrained by the data availability, I examined pay differential on the individual level and industry level, and find empirical support to donative labor hypothesis and compensating wage theory.

Although the actualization of altruism does not have to depend on the industry or occupation, industries and occupations present as an important context for employment and wage setting. Applying CCREM, I have been able to estimate an average donative labor effect as well as the full array of industry and occupation effects. Acknowledging the variability on industry and occupation levels is important to dispel the misperception that nonprofit workers in some industries are “less altruistic” than others because effects from different sources (industry, occupation, and individual) are decomposed. The resultant inventory of nonprofit wage differentials across industries and occupations can be used for reference and corroboration for future nonprofit wage study.

The effects of commercialism have been examined in other areas, such as financial health or nonprofit mission drift. I have extended the definition and measure of commercialism in the context of the sectoral pay differentials. Taking advantage of detailed human capital and demographic information from ACS and Census data, I have tested different commercialism measures generated from SOI data. Finding of this part helps elucidate the meaning of commercialism. Treating commercialism as intent rather than a result seems more relevant to the sectoral pay differential study. As an inverse proxy for commercialism, fundraising efforts predict lower pay for workers. Measured as a compositional effect, commercialism – the for-profit share of workers – increases employee salary. Commercialism affects pay due to its associated focus on efficiency and cost minimization mindset and potential subsequent change work environment and management practices. The consistent effects of commercialism in its compositional and substantive forms have advanced our knowledge about the relationship between commercialism and pay.

**Limitations and gaps for future study**

My dissertation has tested and lent support to donative labor theory, compensating wage theory, and possibly efficiency wage theory. Corroborating the random effects of nonprofit wage differential across industries and occupations with previous studies shows that the estimates are reliable. There are several limitations or gaps that future researches might address.

I have modeled the random effects of nonprofit pay differential on the industry level but have not offered an explanation. Past researches have tried to explain the positive nonprofit pay differential through attenuated property rights theory (Preston, 1988). However, it cannot explain why nonprofits with the same non-distribution constraints pay less than for-profits in other industries. Similarly, Jones's (2015) application of supply and demand of altruistic workers on the industry level cannot explain why, in industries where the supply is not enough, the sectoral pay differential is not zero when nonprofit and for-profits compete for same-type of workers.

The majority of nonprofit pay studies mentioned the efficiency wage theory, but few tested it. A major reason might be limited data since the application of efficiency wage is on the firm and industry levels. The data generation process in the multilevel modeling makes it possible to make the try because it can explicitly model the industry level variability. My tentative explanation for the random effects of nonprofit pay differential is that the sector dominates the industry pays higher than the other sector. Future studies could consider the relationship between organization size and pay on the industry level because large organizations -- no matter whether it is nonprofit or for-profit -- usually pay higher, which is related to the difficulty in supervision. That large organizations dominate an industry seems common. In 2015, 210,670 nonprofits (66.9 percent) had expenses lower than $500,000, but they only composed 2 percent of the total public charity expenditures. In contrast, only 5.3 percent of organizations have expenses over $10 million, but they account for 87.7 percent of expenditures of public charity (McKeever, 2018). Similarly, more commercialized industries, which are dominated by for-profits, are more likely to see larger for-profit firms than nonprofits.

The dissertation does not cover the organizational level analysis due to the lack of organization data. It means I did not examine hypotheses that might be originated from attenuated property rights theory, such as what Preston (1988) and Byrne (2014) do. Organizational level data only exist in limited scenarios such as hospitals (Roomkin & Weisbrod, 1999), nursing home, childcare centers (Ben-Ner et al., 2011). It might remain challenging to have nationally representative data that also contains information of individuals for control.

Another limitation relates to the pattern of the variation on the occupation level. In addition to the inter-industry dispersion, I have modeled the size and range of inter-occupation wage dispersion as residuals after controlling human capital, demographic background, industry, and state effects. Ability bias explains part of the variability on the occupation level, but remarkable wage dispersion (random intercept) and nonprofit wage differentials (random slope) are present. The dispersion on the occupation level can be tested with information on job skill requirements and work conditions. Hirsch (2005) has insightful discussions on the application of occupation variables. Future studies can examine the occupation wage dispersion with more occupation level variables.

Commercialism effect on pay is built on compensating wage theory with the rationale that commercialized industries have less desirable working conditions than less commercialized industries. Commercialism is measured as the percentage of for-profit workers as well as the inverse percentage of fundraising expenses in the total expenses. Both measures confirm the effect of commercialism to increase pay. However, the argument is mostly based on the review of the literature and entails some assumptions. Future studies could explore what changes are to the work conditions and management practices as a result of commercialism. In addition, both measures might be subject to measurement errors. By limiting the 289 industries in ACS data to 58 industries, the measurement error of the for-profit share of workers is reduced. The measure of fundraising efforts might have more measurement errors. More than half of the industries have very minimal fundraising expenses, which may not differentiate the industries well.

**Conclusion**

Nonprofit pay study is an important topic in two senses. The nonprofit sector employs a large number of workers. Most services provided nonprofits are labor-intensive and require close human engagement. Nonprofit pay study is thus an informative avenue to understand the nonprofit sector. Secondly, the nonprofit pay study is not a new area. However, findings in current studies contradict one another on whether nonprofits pay better than for-profit organizations. The discordance in findings suggests a disconnection between theoretical predictions and empirical evidence. From the perspective of knowledge building, more research efforts and empirical evidence are needed to either offer support to theories or to falsify theories.

With this in mind, I employ a multilevel approach to deconstruct theories and analyze nationally representative economy-wide data to reveal a panorama view of nonprofit pay differentials relative to the for-profit sector. By controlling the occupation and state effects, I have analyzed and presented how nonprofit pay differentials are situated in the inter-industry pay dispersion. The finding offers a comprehensive view of the nonprofit pay differential. For instance, industries where nonprofits have positive differential are often low-paying industries such as childcare centers. By removing differences in higher-level structures (industries, occupations, and state), the CCREM models produce a negative 5.7 percent differential for nonprofits, which I argue as donative labor effect. By examining the industries through the lens of commercialism, I have found support in compensating wage theory and confirmed the moderating effect of commercialism on the gender pay gap and the manager-staff pay gap.

My endeavor not only contributes to a coordinated explanation of theories on differential levels, but also establishes an exhaustive inventory of nonprofit pay differential as a composite of industry effect, occupation effect, and individual effect. In the meantime, I have listed potential research directions for future studies that include testing the efficiency wage theory.

# Appendices

## *Appendix A. Data cleaning process*

| | Steps | Nonprofit | For-profit | Total |
|---|---|---|---|---|
| 1. | Combined datasets in 13 years | 1,758,404 (4.32%) | 14,307,394 (35.11%) | 40,745,671 (9 categories)* |
| 2. | Keep full-time adult workers in 51 states (16=<age=<65) (weeks working = 50-52 weeks) | 898,515 (7.81%) | 7,556,504 (65.67%) | 11,506,431 (9 categories) |
| 3. | Keep only for-profit and nonprofit | 898,515 (10.63%) | 7,556,504 (89.37%) | 8,455,019 |
| 4. | Drop observations with imputed variables (incwage, age, sex, race, ind, occ, workhours, classwork) | 883,716 (10.65%) | 7,411,542 (89.35%) | 8,295,258 |
| 5. | Keep 58 industries | 664,820 (22.03%) | 2,353,305 (77.97%) | 3,018,125 |
| 6. | Drop occupation with no nonprofit presence | 664,820 (%) | 2,353,109 (77.97%) | 3,017,929 |
| 7. | Drop if log(income)<8 | 664,662 (22.03%) | 2,352,570 (77.97%) | 3,017,232 |
| 8. | Drop several occupations with merge problem | 664,646 (22.03%) | 2,352,464 (99.97%) | 3,017,110 |

* 9 categories: N/A, self-employed (not incorporated), self-employed (incorporated), for-profit, nonprofit, the federal government, state government, local government, unpaid family workers.

## *Appendix B. Industry categories between ACS and SOI*

| Industry (58 categories) | NAICS in ACS | NAICS in SOI | Combined title | Combined industry code |
|---|---|---|---|---|
| Support activities for agriculture and forestry | 115 | 115000, 115110, 115210 | Food and agricultural programs | 1150 |
| Electric power generation, transmission and distribution | 2211P | 221000 | Public utilities | 2210 |
| Natural gas distribution | 2212P | | | |
| Sewage treatment facilities | 22132 | | | |
| Water, steam, air conditioning, and irrigation systems | 2213M | | | |
| Electric and gas, and other combinations | 221MP | | | |
| Not specified utilities | 22S | | | |
| Air transportation | 481 | 480000 | Transportation | 4800 |
| Rail transportation | 482 | | | |
| Water transportation | 483 | | | |
| Truck transportation | 484 | | | |
| Taxi and limousine service | 4853 | | | |
| Bus service and urban transit | 485M | | | |
| Pipeline transportation | 486 | | | |
| Scenic and sightseeing transportation | 487 | | | |
| Services incidental to transportation | 488 | | | |
| Newspaper publishers | 51111 | 511100 | Newspaper, periodical, book, and database Publishers | 5111 |
| Periodical, book, and directory publishers | 5111Z | | | |
| Motion pictures and video industries | 5121 | 512110 | Religious film & video | 5121 |
| Sound recording industries | 5122 | | | |
| Radio and television broadcasting, telecommunication | 513M | 513110, 513120, 513300 | Radio and television broadcasting, telecommunication | 5131 |
| Other information services | 51412 | 514120 | Libraries and Archives | |

| Industry (58 categories) | NAICS in ACS | NAICS in SOI | Combined title | Combined industry code |
|---|---|---|---|---|
| Undefined | 5141Z | | | 5141 |
| Savings institutions, including credit unions | 5221M | 522130 | Credit unions | 5221 |
| Non-depository credit and related activities | 522M | | | |
| Insurance carriers and related activities | 524 | 524110, 524113, 524114 | Insurance providers | 5241 |
| Banking and related activities | 52M1 | 522000 | Financial institutions | 5220 |
| Securities, commodities, funds, trusts, and other financial investments | 52M2 | | | |
| Real estate | 531 | 531390 | Real estate associations | 5313 |
| Legal services | 5411 | 541199 | Crime prevention, rehabilitation, law enforcement, inmate support | 5411 |
| Management, scientific and technical consulting services | 5416 | 541618 | Management & technical assistance | 5416 |
| Scientific research and development services | 5417 | 541710, 541720 | Research institute | 5417 |
| Veterinary services | 54194 | 541940 | Veterinary Services | 5419 |
| Employment services | 5613 | 561310 | Employment services | 5613 |
| Elementary and secondary schools | 6111 | 611110 | Elementary and secondary schools | 6111 |
| Colleges, universities, and professional schools, including junior colleges | 611M1 | 611210, 611310 | Two-year college and higher education | 6112 |
| Business, technical, and trade schools and training | 611M2 | 611510 | Vocational & Technical Schools + Business, technical, and trade schools and training | 6115 |
| Other schools, instruction and educational services | 611M3 | 611000, 611610, 611620, 611699, 611710 | Other schools, instruction and educational services | 6116 |
| Office of chiropractors | 62131 | 621340 | Rehabilitative care | 6213 |
| Offices of optometrists | 62132 | | | |
| Offices of other health practitioners | 6213ZM | | | |
| Outpatient care centers | 6214 | 621410, 621420, 621491, 621498 | Outpatient care centers | 6214 |

| Industry (58 categories) | NAICS in ACS | NAICS in SOI | Combined title | Combined industry code |
|---|---|---|---|---|
| Home health care services | 6216 | 621610 | Home health care | 6216 |
| Other health care services | 621M | 621910, 621911, 621999 | Other health care services | 6219 |
| Hospitals | 622 | 622110, 622210, 622310 | Hospitals | 6220 |
| Nursing care facilities | 6231 | 623110 | Nursing facilities, hospices | 6231 |
| Residential care facilities, except skilled nursing facilities | 623M | 632220, 623311, 623312, 623990 | Residential care facilities | 6322 |
| Individual and family services | 6241 | 624100, 624110, 624120, 624190 | Individual and family services | 6241 |
| Community food and housing, and emergency services | 6242 | 624210, 624220, 624221, 624229, 624230 | Community food and housing | 6242 |
| Vocational rehabilitation services | 6243 | 624310 | Vocational Counseling, Employment, Job Training | 6243 |
| Child day care services | 6244 | 624410 | Day care centers | 6244 |
| Performing arts, spectator sports, and related industries | 711 | 711100, 711110, 711120, 711130 | Performing arts, spectator sports, and related industries | 7111 |
| Museums, art galleries, historical sites, and similar institutions | 712 | 712110, 712120, 712130, 712190 | Museums, art galleries, historical sites | 7121 |
| Other amusement, gambling, and recreation industries | 713Z | 713940, 713990 | Other amusement, gambling, and recreation industries | 7139 |
| Traveler accommodation | 7211 | 721199 | All other traveler accommodation | 7211 |
| Recreational vehicle parks and camps, and rooming and boarding houses | 721M | 721214 | Recreational and vacation camps | 7212 |
| Funeral homes, cemeteries and crematories | 8122 | 812220 | Cemeteries | 8122 |
| Other personal services | 8129 | 812910 | Animal training | 8129 |

### *Appendix C. Variable selection models*

| | Natural log of annual income | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| For-profit share | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (3.609) | (3.498) | (2.700) | (3.155) |
| Female percentage | -0.001 | -0.001 | -0.001 | -0.001 |
| | (-1.448) | (-1.226) | (-1.448) | (-1.437) |
| Nonprofit | -0.057*** | -0.049*** | -0.057*** | -0.049*** |
| | (-3.932) | (-3.547) | (-3.932) | (-3.543) |
| Female | -0.185*** | -0.186*** | -0.185*** | -0.186*** |
| | (-272.934) | (-272.825) | (-272.933) | (-272.825) |
| Years of education | 0.073*** | 0.073*** | 0.073*** | 0.073*** |
| | (468.676) | (467.171) | (468.677) | (467.180) |
| Latino | -0.063*** | -0.063*** | -0.063*** | -0.063*** |
| | (-57.061) | (-57.015) | (-57.061) | (-57.015) |
| Black | -0.093*** | -0.093*** | -0.093*** | -0.093*** |
| | (-90.402) | (-90.341) | (-90.402) | (-90.342) |
| Asian | -0.029*** | -0.030*** | -0.029*** | -0.030*** |
| | (-21.799) | (-21.898) | (-21.799) | (-21.897) |
| Other races | -0.066*** | -0.066*** | -0.066*** | -0.066*** |
| | (-32.353) | (-32.316) | (-32.353) | (-32.316) |
| Speak English | 0.045*** | 0.045*** | 0.045*** | 0.045*** |
| | (44.654) | (44.384) | (44.654) | (44.383) |
| Work experience | 0.011*** | 0.011*** | 0.011*** | 0.011*** |
| | (449.154) | (447.659) | (449.154) | (447.658) |
| Work experience squared | -0.053*** | -0.053*** | -0.053*** | -0.053*** |
| | (-266.868) | (-265.419) | (-266.868) | (-265.419) |
| Work hours per week | 0.013*** | 0.013*** | 0.013*** | 0.013*** |
| | (342.443) | (341.053) | (342.443) | (341.053) |
| Female percentage squared | | -0.062 | | |
| | | (-0.344) | | |
| For-profit share squared | | | 0.180 | |
| | | | (0.492) | |
| Trend of for-profit share | | | | 0.119 |
| | | | | (0.593) |
| Random slope of nonprofit | Yes | Yes | Yes | Yes |
| Constant | 10.673*** | 10.674*** | 10.662*** | 10.664*** |
| | (378.535) | (330.193) | (300.269) | (355.658) |
| Observations | 3,017,110 | 2,997,875 | 3,017,110 | 2,997,875 |
| Akaike Inf. Crit. | 4,065,931 | 4,035,721 | 4,065,933 | 4,035,720 |
| Bayesian Inf. Crit. | 4,066,215 | 4,036,018 | 4,066,230 | 4,036,017 |
| *Note:* | | | | *p**p***p<0.01 |

## *Appendix D. Industry information and estimates*

| Industry name | Industry code | Number of for-profit workers | Number of nonprofit workers | Total | For-profit share of workers | Random intercept | Random slope for nonprofit |
|---|---|---|---|---|---|---|---|
| Food and agricultural programs | 1150 | 6,791 | 274 | 7,065 | 0.96 | -0.0636 | -0.0400 |
| Public utilities | 2210 | 94,027 | 8,782 | 102,809 | 0.91 | 0.3029 | -0.0528 |
| Transportation | 4800 | 262,258 | 5,002 | 267,260 | 0.98 | 0.0616 | 0.0401 |
| Newspaper, periodical, book, and database Publishers | 5111 | 56,619 | 2,550 | 59,169 | 0.96 | -0.0114 | 0.0226 |
| Religious film & video | 5121 | 17,939 | 975 | 18,914 | 0.95 | 0.0069 | -0.2033 |
| Radio and television broadcasting, telecommunication | 5131 | 12,348 | 605 | 12,953 | 0.95 | 0.0429 | -0.1259 |
| Libraries and Archives | 5141 | 5,500 | 782 | 6,282 | 0.88 | 0.0978 | -0.1529 |
| Financial institutions | 5220 | 293,501 | 5,048 | 298,549 | 0.98 | 0.1735 | 0.0526 |
| Credit unions | 5221 | 89,632 | 14,837 | 104,469 | 0.86 | 0.1088 | -0.0572 |
| Insurance providers | 5241 | 219,292 | 15,488 | 234,780 | 0.93 | 0.1690 | 0.0863 |
| Real estate associations | 5313 | 111,532 | 6,295 | 117,827 | 0.95 | -0.0185 | -0.0459 |
| Crime prevention, rehabilitation, law enforcement, inmate support | 5411 | 106,522 | 3,490 | 110,012 | 0.97 | 0.0639 | -0.1906 |
| Management & technical assistance | 5416 | 80,616 | 2,483 | 83,099 | 0.97 | 0.1467 | -0.0792 |
| Research institute | 5417 | 35,676 | 11,946 | 47,622 | 0.75 | 0.2492 | -0.0222 |
| Veterinary Services | 5419 | 17,225 | 466 | 17,691 | 0.97 | -0.1857 | 0.0076 |
| Employment services | 5613 | 37,954 | 1,990 | 39,944 | 0.95 | -0.0962 | -0.0782 |
| Elementary and secondary schools | 6111 | 50,435 | 79,531 | 129,966 | 0.39 | -0.0239 | 0.0843 |
| Two-year college and higher education | 6112 | 48,165 | 76,142 | 124,307 | 0.39 | 0.0633 | 0.1070 |
| Vocational & Technical Schools + Business, technical, and trade schools and training | 6115 | 5,413 | 1,215 | 6,628 | 0.82 | -0.0056 | -0.0331 |
| Other schools, instruction and educational services | 6116 | 10,908 | 6,436 | 17,344 | 0.63 | 0.0157 | 0.0386 |
| Rehabilitative care | 6213 | 18,122 | 1,377 | 19,499 | 0.93 | -0.1023 | 0.0845 |
| Outpatient care centers | 6214 | 51,963 | 26,499 | 78,462 | 0.66 | 0.0167 | 0.00251 |

| Industry name | Industry code | Number of for-profit workers | Number of nonprofit workers | Total | For-profit share of workers | Random intercept | Random slope for nonprofit |
|---|---|---|---|---|---|---|---|
| Home health care | 6216 | 35,611 | 8,421 | 44,032 | 0.81 | -0.1091 | 0.07954 |
| Other health care services | 6219 | 63,838 | 21,087 | 84,925 | 0.75 | 0.0942 | 0.06394 |
| Hospitals | 6220 | 252,313 | 226,694 | 479,007 | 0.53 | 0.1310 | 0.10195 |
| Nursing facilities, hospices | 6231 | 93,572 | 25,215 | 118,787 | 0.79 | -0.0665 | 0.05238 |
| Residential care facilities | 6232 | 27,745 | 19,189 | 46,934 | 0.59 | -0.1039 | 0.03939 |
| Individual and family services | 6241 | 17,032 | 38,714 | 55,746 | 0.31 | -0.0254 | 0.07480 |
| Community food and housing | 6242 | 871 | 5,843 | 6,714 | 0.13 | 0.0314 | -0.01528 |
| Vocational Counseling, Employment, Job Training | 6243 | 3,291 | 6,565 | 9,856 | 0.33 | -0.0459 | -0.02934 |
| Day care centers | 6244 | 33,363 | 16,130 | 49,493 | 0.67 | -0.2622 | 0.08409 |
| Performing arts, spectator sports, and related industries | 7110 | 15,055 | 4,048 | 19,103 | 0.79 | -0.0064 | -0.12637 |
| Museums, art galleries, historical sites | 7121 | 1,922 | 7,935 | 9,857 | 0.19 | 0.0320 | 0.08194 |
| Other amusement, gambling, and recreation industries | 7139 | 73,021 | 7,224 | 80,245 | 0.91 | -0.1015 | 0.05072 |
| All other traveler accommodation | 7211 | 82,663 | 1,169 | 83,832 | 0.99 | -0.1093 | 0.02065 |
| Recreational and vacation camps | 7212 | 1,853 | 2,015 | 3,868 | 0.48 | -0.2227 | -0.00513 |
| Cemeteries | 8122 | 7,520 | 787 | 8,307 | 0.91 | -0.0632 | 0.07182 |
| Other personal service, animal training | 8129 | 10,356 | 1,397 | 11,753 | 0.88 | -0.1844 | 0.01001 |

*Appendix E. Random effects of nonprofit over occupations*

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 4 | Chief executives and public administrators | 33,213 | 30.74 | 0.7899 | -0.0495 |
| 7 | Financial managers | 79,015 | 55.13 | 0.3175 | 0.0608 |
| 8 | Human resources and labor relations managers | 14,600 | 67.02 | 0.3610 | -0.0066 |
| 13 | Managers and specialists in marketing, advertising, and public relation | 35,835 | 56.2 | 0.3594 | -0.0957 |
| 14 | Managers in education and related fields | 36,354 | 66.27 | 0.2246 | 0.0236 |
| 15 | Managers of medicine and health occupations | 43,430 | 70.5 | 0.3821 | 0.0167 |
| 17 | Managers of food-serving and lodging establishments | 12,888 | 51.39 | 0.0933 | 0.0440 |
| 18 | Managers of properties and real estate | 29,481 | 57.82 | 0.1298 | 0.0131 |
| 19 | Funeral directors | 3,029 | 21.23 | 0.0938 | -0.0571 |
| 21 | Managers of service organizations | 17,796 | 68.31 | 0.2448 | -0.0366 |
| 22 | Managers and administrators | 134,089 | 40.59 | 0.3396 | -0.0510 |
| 23 | Accountants and audit | 60,733 | 60.85 | 0.2173 | 0.0106 |
| 24 | Insurance underwriter | 10,847 | 66.95 | 0.1779 | -0.0492 |
| 25 | Other financial specialists | 70,709 | 44.8 | 0.2561 | -0.1348 |
| 26 | Management analysts | 28,550 | 42.1 | 0.3737 | -0.1268 |
| 27 | Personnel, HR, training | 33,459 | 73.7 | 0.2250 | -0.0679 |
| 28 | Purchasing agents and buyers, of farm products | 5 | 80 | 0.2395 | -0.0229 |
| 29 | Buyers, wholesale and retail trade | 73 | 54.79 | -0.2697 | 0.0532 |
| 33 | Purchasing managers, agents and buyers | 9,033 | 55.03 | 0.1275 | -0.0574 |
| 34 | Business and promotion agents | 1,674 | 44.38 | 0.2353 | -0.1637 |
| 35 | Construction inspectors | 444 | 15.99 | -0.0382 | 0.0724 |
| 36 | Inspectors and compliance officers | 6,457 | 62.03 | 0.2546 | 0.0415 |
| 37 | Management support occupations | 6,635 | 67.66 | 0.1462 | -0.0061 |
| 43 | Architects | 862 | 23.55 | 0.3956 | -0.0388 |
| 44 | Aerospace engineer | 537 | 11.73 | 0.3166 | 0.0451 |
| 45 | Metallurgical and material engineers | 94 | 21.28 | 0.1941 | -0.0099 |
| 47 | Petroleum, mining engineers | 119 | 10.08 | 0.4441 | -0.0684 |
| 48 | Chemical engineers | 213 | 14.08 | 0.2352 | -0.0555 |
| 53 | Civil engineers | 1,171 | 9.91 | 0.2474 | -0.0544 |
| 55 | Electrical engineer | 4,427 | 10.19 | 0.2489 | 0.0570 |
| 56 | Industrial engineers | 1,359 | 23.84 | 0.2443 | 0.0756 |
| 57 | Mechanical engineers | 1,280 | 5.55 | 0.2178 | -0.0107 |
| 59 | Not-elsewhere-classified engineers | 8,932 | 12.36 | 0.2680 | 0.0561 |
| 64 | Computer systems analysts | 59,613 | 33.81 | 0.2431 | -0.0018 |
| 65 | Operations and system researchers and analysts | 5,404 | 45.36 | 0.2152 | 0.0774 |
| 66 | Actuaries | 2,580 | 32.29 | 0.6284 | -0.0789 |
| 68 | Mathematicians and mathematical scientists | 1,607 | 46.73 | 0.2935 | -0.0678 |
| 69 | Physicists and astronomers | 584 | 16.61 | 0.2013 | -0.0372 |
| 73 | Chemists | 2,011 | 37.54 | 0.0479 | -0.0924 |
| 74 | Atmospheric and space scientists | 172 | 18.02 | 0.1759 | -0.0262 |
| 75 | Geologists | 1,580 | 29.24 | 0.0343 | -0.0920 |
| 76 | Physical scientists, n. e. .c | 8,449 | 39.82 | 0.0593 | -0.1319 |
| 77 | Agricultural and food scientists | 646 | 25.85 | 0.0066 | -0.0704 |
| 78 | Biological scientists | 2,803 | 50.95 | 0.0205 | -0.1289 |
| 79 | Foresters and conservations scientists | 415 | 7.71 | 0.0280 | 0.0000 |

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 83 | Medical scientists | 6,740 | 50.88 | 0.0807 | -0.0767 |
| 84 | Physicians | 35,000 | 36.17 | 0.7344 | -0.0480 |
| 85 | Dentists | 289 | 42.21 | 0.3956 | 0.2283 |
| 86 | Veterinarians | 4,048 | 60.97 | 0.4891 | -0.1371 |
| 87 | Optometrists | 991 | 41.57 | 0.6498 | -0.0628 |
| 88 | Podiatrists | 259 | 28.96 | 0.5718 | -0.0973 |
| 89 | Other health and therapy | 1,137 | 31.93 | 0.1206 | 0.0341 |
| 95 | Registered nurses | 193,429 | 89.7 | 0.4253 | -0.0006 |
| 96 | Pharmacists | 6,540 | 52.91 | 0.6509 | -0.0089 |
| 97 | Dietitians and nutritionists | 4,252 | 91.06 | 0.0849 | 0.0180 |
| 98 | Respiratory therapist | 8,728 | 60.84 | 0.2529 | -0.0252 |
| 99 | Occupational therapists | 5,958 | 85.99 | 0.4444 | -0.0959 |
| 103 | Physical therapists | 17,653 | 66.34 | 0.3399 | -0.0305 |
| 104 | Speech therapists | 4,282 | 91.55 | 0.4150 | -0.0919 |
| 105 | Therapists, n.e.c | 8,186 | 76.03 | 0.1298 | -0.0589 |
| 106 | Physicians' assistant | 4,322 | 61.2 | 0.4496 | -0.0120 |
| 154 | Subject instructors (HS/college) | 41,473 | 45.86 | 0.0501 | 0.0767 |
| 155 | Kindergarten and earlier school teachers | 21,822 | 97.98 | -0.1208 | 0.0126 |
| 156 | Primary school teachers | 52,857 | 77.14 | 0.0679 | -0.0323 |
| 157 | Secondary school teachers | 12,247 | 54.01 | 0.0858 | -0.0402 |
| 158 | Special education teachers | 2,790 | 84.98 | 0.0877 | 0.0182 |
| 159 | Teachers, n.e.c | 25,472 | 72.86 | -0.1365 | -0.0539 |
| 163 | Vocational and educational counselors | 24,480 | 69.2 | -0.0126 | -0.0232 |
| 164 | Librarians | 3,730 | 76.51 | -0.0070 | 0.0334 |
| 165 | Archivists and curators | 2,003 | 60.91 | 0.0086 | 0.1115 |
| 166 | Economists, market researchers | 6,729 | 57.13 | 0.3142 | -0.0301 |
| 167 | Psychologists | 4,390 | 63.64 | 0.0846 | 0.0067 |
| 169 | Social scientists, n.e.c | 1,249 | 54.04 | -0.0380 | 0.0630 |
| 173 | Urban and regional planners | 149 | 41.61 | 0.2726 | 0.0278 |
| 174 | Social workers | 34,900 | 81.27 | 0.0597 | -0.0129 |
| 175 | Recreation workers | 10,494 | 64.74 | -0.1063 | -0.0238 |
| 176 | Clergy and religious workers | 1,660 | 36.99 | -0.2378 | 0.0250 |
| 178 | Lawyers | 46,026 | 34.89 | 0.5477 | -0.2213 |
| 183 | Writers and authors | 3,894 | 55.08 | 0.0992 | 0.0542 |
| 184 | Technical writers | 1,546 | 59.57 | 0.1638 | -0.0050 |
| 185 | Designers | 8,283 | 50.79 | 0.0637 | 0.0395 |
| 186 | Musician or composer | 952 | 26.37 | -0.0044 | 0.2678 |
| 187 | Actors, directors, producers | 5,356 | 38.85 | 0.1759 | -0.1846 |
| 188 | Art makers: painters, sculptors, craft-artists, and print-makers | 2,722 | 34.42 | 0.1454 | -0.1244 |
| 189 | Photographers | 1,201 | 23.98 | -0.0933 | 0.0583 |
| 193 | Dancers | 253 | 80.63 | 0.0300 | -0.1094 |
| 194 | Art/entertainment performers | 1,464 | 54.51 | -0.0467 | -0.1098 |
| 195 | Editors and reporters | 16,347 | 46.23 | 0.0656 | 0.0384 |
| 198 | Announcers | 761 | 18.53 | -0.1184 | -0.0156 |
| 199 | Athletes, sports instructors | 6,117 | 21.4 | -0.0251 | -0.0948 |
| 203 | Clinical laboratory technicians | 22,721 | 74.44 | 0.0703 | 0.0549 |
| 204 | Dental hygienists | 97 | 90.72 | 0.2884 | 0.0407 |
| 205 | Health record tech specialists | 7,009 | 91.51 | -0.1189 | 0.0191 |
| 206 | Radiologic tech specialists | 21,480 | 68.96 | 0.2935 | 0.0213 |
| 207 | Licensed practical nurses | 38,739 | 91.36 | 0.0867 | -0.0213 |
| 208 | Health technologists | 18,455 | 45.98 | -0.0817 | 0.0541 |
| 214 | Engineering technicians | 9,921 | 34.02 | -0.0228 | -0.0525 |

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 217 | Drafters | 989 | 23.05 | 0.0008 | 0.0193 |
| 218 | Surveyors, cartographers | 692 | 23.99 | -0.0534 | 0.0285 |
| 223 | Biological technician | 878 | 47.49 | -0.0403 | -0.0880 |
| 224 | Chemical technicians | 597 | 29.82 | -0.0742 | -0.0587 |
| 225 | Other science technic | 213 | 22.54 | 0.1451 | -0.0109 |
| 226 | Airplane pilots and navigators | 8,012 | 4.44 | 0.4076 | -0.1442 |
| 227 | Air traffic controllers | 830 | 24.7 | 0.1662 | -0.0912 |
| 228 | Broadcast equipment operators | 2,324 | 10.11 | 0.0047 | 0.0047 |
| 229 | Computer software developers | 33,888 | 27.32 | 0.3733 | -0.0321 |
| 233 | Programmers of numerically controlled machines tools | 71 | 12.68 | -0.0682 | 0.0140 |
| 234 | Legal assistants, paralegals | 34,663 | 86.41 | 0.0394 | 0.0544 |
| 243 | Supervisors and proprietors of sales jobs | 34,448 | 51.15 | 0.3012 | -0.0832 |
| 253 | Insurance sales occupations | 37,249 | 52.66 | 0.0825 | 0.0087 |
| 254 | Real estate sales occupations | 25,486 | 51.03 | 0.1612 | 0.0480 |
| 255 | Financial services sales occupations | 26,680 | 33.11 | 0.3987 | -0.2188 |
| 256 | Advertising and related sales jobs | 7,476 | 59.46 | 0.2385 | -0.0162 |
| 258 | Sales engineers | 129 | 8.53 | 0.3199 | -0.0487 |
| 274 | Salespersons, n.e.c | 21,935 | 48.29 | 0.2488 | 0.0723 |
| 275 | Retail sales clerks | 1,981 | 55.33 | 0.1477 | -0.1130 |
| 276 | Cashiers | 9,622 | 70.41 | -0.1920 | 0.0284 |
| 277 | Door-to-door sales, street sales, and news vendors | 1,070 | 38.32 | -0.4421 | 0.0071 |
| 283 | Sales demonstrators /promoters / models | 130 | 50.77 | 0.1347 | -0.0733 |
| 303 | Office supervisors | 50,260 | 73.82 | 0.0954 | 0.0564 |
| 308 | Computer and peripheral equipment operators | 4,819 | 53.02 | -0.0519 | 0.0766 |
| 313 | Secretaries | 118,840 | 96.78 | -0.0436 | 0.0178 |
| 315 | Typists | 8,830 | 90.4 | -0.1206 | 0.0532 |
| 316 | Interviewers, enumerators and surveyors | 10,363 | 83.05 | -0.1138 | -0.0267 |
| 317 | Hotel clerks | 5,977 | 65.42 | -0.3530 | 0.0425 |
| 318 | Transportation ticket and reservation agents | 8,325 | 60.72 | -0.0493 | 0.0269 |
| 319 | Receptionists | 26,563 | 92.85 | -0.2162 | 0.0555 |
| 326 | Correspondence and order clerks | 1,540 | 70.06 | -0.1374 | 0.0085 |
| 328 | Human resources clerk | 1,272 | 91.67 | -0.0166 | 0.0548 |
| 329 | Library assistants | 1,265 | 77.79 | -0.2398 | -0.0388 |
| 335 | File clerks | 8,610 | 79.9 | -0.1664 | 0.0846 |
| 336 | Records clerks | 4,993 | 86.42 | -0.0136 | 0.0302 |
| 337 | Bookkeepers and accounting clerks | 37,599 | 86.54 | -0.0485 | 0.1008 |
| 338 | Payroll and timekeeping clerks | 5,042 | 90.08 | 0.0377 | 0.0534 |
| 344 | Billing clerks and related financial records processing | 16,916 | 90.58 | -0.0919 | -0.0100 |
| 347 | Office machine operators | 1,225 | 66.12 | -0.3151 | 0.0884 |
| 348 | Telephone operators | 2,294 | 87.45 | -0.2248 | 0.0325 |
| 349 | Other telecom operators | 209 | 60.29 | -0.0006 | 0.0474 |
| 356 | Mail clerks, outside of post office | 2,885 | 47.9 | -0.3583 | 0.0479 |
| 357 | Messengers | 2,338 | 24.68 | -0.3945 | -0.0310 |
| 359 | Dispatchers | 8,343 | 42.62 | -0.1487 | -0.0351 |
| 364 | Shipping and receiving clerks | 4,670 | 29.76 | -0.2395 | -0.0445 |
| 365 | Stock and inventory clerks | 6,223 | 42.46 | -0.2020 | -0.0173 |
| 366 | Meter readers | 2,095 | 16.95 | -0.2460 | 0.0247 |
| 368 | Weighers, measurers, and checkers | 838 | 45.11 | -0.0597 | 0.0148 |
| 373 | Material recording, scheduling, production, planning, and expediting clerks | 12,050 | 48.36 | 0.0289 | -0.0628 |

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 375 | Insurance adjusters, examiners, and investigators | 51,278 | 72.13 | -0.0469 | -0.0403 |
| 376 | Customer service reps | 62,792 | 76.14 | -0.1063 | 0.0539 |
| 377 | Eligibility clerks for government programs | 544 | 86.58 | -0.0464 | 0.0287 |
| 378 | Bill and account collectors | 7,011 | 74.18 | -0.1107 | 0.0373 |
| 379 | General office clerks | 26,772 | 86.33 | -0.1415 | 0.0564 |
| 383 | Bank tellers | 29,299 | 89 | -0.3397 | 0.2294 |
| 384 | Proofreaders | 381 | 71.92 | -0.2120 | 0.0607 |
| 385 | Data entry keyers | 12,128 | 83.6 | -0.1955 | 0.0813 |
| 386 | Statistical clerks | 741 | 67.88 | 0.0419 | 0.0194 |
| 389 | Administrative support jobs | 20,435 | 79.81 | -0.0045 | 0.0451 |
| 405 | Housekeepers, maids, butlers, stewards, and lodging quarters cleaners | 30,791 | 83.67 | -0.2981 | -0.0446 |
| 415 | Supervisors of guards | 1,822 | 13.78 | -0.0028 | 0.0111 |
| 417 | Firefighting, prevention | 260 | 8.85 | -0.0167 | -0.0042 |
| 418 | Police, detectives, and private investigators | 2,424 | 47.65 | 0.0244 | 0.1013 |
| 423 | Other law enforcement | 48 | 43.75 | -0.1588 | 0.0130 |
| 425 | Crossing guards and bridge tenders | 58 | 32.76 | -0.1774 | 0.0119 |
| 426 | Guards, watchmen, doorkeepers | 13,214 | 18.67 | -0.2517 | 0.0412 |
| 427 | Protective services | 693 | 47.04 | -0.4349 | 0.0632 |
| 434 | Bartenders | 2,672 | 38.59 | -0.2114 | -0.1239 |
| 435 | Waiter/waitress | 5,103 | 61.41 | -0.1439 | -0.0630 |
| 436 | Cooks, variously defined | 26,291 | 53.44 | -0.1866 | -0.0117 |
| 439 | Kitchen workers | 194 | 72.16 | -0.3343 | 0.0556 |
| 443 | Waiter's assistant | 7,054 | 63.48 | -0.2949 | -0.0600 |
| 444 | Miscellaneous food prep worker | 4,537 | 55.74 | -0.3288 | -0.0700 |
| 445 | Dental assistants | 301 | 94.35 | -0.0736 | -0.0080 |
| 446 | Health aides, except nursing | 28,132 | 87.11 | -0.1518 | 0.0367 |
| 447 | Nursing aides, orderlies and attendants | 110,958 | 86.28 | -0.2403 | 0.0419 |
| 448 | Supervisors of cleaning and building services | 6,863 | 49.69 | -0.0574 | 0.1224 |
| 453 | Janitors | 37,710 | 18.29 | -0.2532 | 0.0553 |
| 454 | Elevator operators | 677 | 8.57 | -0.0456 | -0.0440 |
| 455 | Pest control occupations | 71 | 9.86 | -0.1605 | 0.0217 |
| 456 | Supervisors of person | 3,710 | 46.93 | 0.1001 | -0.0395 |
| 457 | Barbers | 17 | 41.18 | -0.1328 | 0.0167 |
| 458 | Hairdressers and cosmetologists | 974 | 94.56 | -0.0210 | -0.0576 |
| 459 | Recreation facility attendants | 9,100 | 46.23 | -0.0305 | -0.1235 |
| 461 | Guides | 545 | 40.92 | -0.3764 | 0.0884 |
| 462 | Ushers | 502 | 30.88 | -0.3139 | 0.1199 |
| 463 | Public transportation | 6,829 | 54.34 | -0.0475 | 0.0214 |
| 464 | Baggage porters | 3,777 | 18.32 | -0.2709 | 0.0827 |
| 465 | Welfare service aides | 6,545 | 78.87 | -0.0397 | -0.0066 |
| 468 | Childcare workers | 18,735 | 90.73 | -0.2033 | 0.0324 |
| 469 | Personal service occupations | 3,624 | 57.45 | -0.1930 | -0.0126 |
| 473 | Farmers (owners and tenants) | 219 | 19.63 | 0.0445 | -0.1160 |
| 475 | Farm managers, except | 247 | 21.86 | 0.0364 | -0.0466 |
| 479 | Farm workers | 2,418 | 25.64 | -0.2424 | 0.1166 |
| 485 | Supervisors of agricultural occupations | 2,162 | 4.39 | 0.0504 | 0.0201 |
| 486 | Gardeners and grounds | 9,103 | 6.13 | -0.2774 | 0.0469 |
| 487 | Animal caretakers except farms | 3,881 | 73.43 | -0.1682 | 0.0445 |
| 488 | Graders and sorters of agricultural products | 186 | 68.82 | -0.2259 | 0.0355 |
| 489 | Inspectors of agricultural products | 22 | 36.36 | -0.0676 | 0.0218 |
| 496 | Timber, logging, and forestry workers | 776 | 17.91 | -0.0871 | -0.0414 |

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 498 | Fishers, hunters, and kindred | 70 | 2.86 | -0.2280 | 0.0567 |
| 503 | Supervisors of mechanics and repairers | 8,855 | 5 | 0.1003 | 0.0033 |
| 505 | Automobile mechanics | 1,691 | 1.83 | -0.0766 | 0.0897 |
| 507 | Bus, truck, and stationary engine mechanics | 8,200 | 0.87 | -0.0645 | 0.0666 |
| 508 | Aircraft mechanics | 8,734 | 2.78 | 0.1348 | -0.0520 |
| 509 | Small engine repairer | 295 | 1.36 | -0.0121 | 0.0044 |
| 514 | Auto body repairers | 199 | 3.02 | -0.0791 | 0.0726 |
| 516 | Heavy equipment and farm equipment mechanics | 2,814 | 1.35 | 0.0655 | -0.0281 |
| 518 | Industrial machinery repairers | 2,683 | 2.98 | 0.0386 | -0.0297 |
| 519 | Machinery maintenance | 369 | 2.98 | -0.1551 | 0.0392 |
| 523 | Repairers of industrial electrical equipment | 1,001 | 2.9 | 0.1081 | 0.0029 |
| 525 | Repairers of data processing equipment | 3,317 | 20.17 | 0.0546 | 0.0243 |
| 526 | Repairers of household appliance | 201 | 3.48 | -0.0852 | -0.0144 |
| 527 | Telecom and line installers | 2,536 | 7.97 | 0.0183 | 0.0782 |
| 533 | Repairers of electric equipment | 532 | 4.32 | 0.1248 | -0.0339 |
| 534 | Heating, air conditioning mechanics | 2,243 | 1.52 | 0.0407 | 0.0232 |
| 535 | Precision makers, repairers | 1,509 | 17.03 | 0.0787 | -0.0340 |
| 536 | Locksmiths and safe repairers | 240 | 5 | 0.0227 | 0.0293 |
| 539 | Repairers of mechanic | 944 | 7.31 | -0.0573 | -0.0484 |
| 543 | Elevator installers and repairers | 54 | 1.85 | 0.2666 | -0.0090 |
| 544 | Millwrights | 215 | 1.86 | 0.0951 | 0.0033 |
| 549 | Mechanics and repairers | 15,574 | 3.09 | -0.1141 | 0.0352 |
| 558 | Supervisors of construction work | 2,467 | 3.73 | 0.1641 | -0.0194 |
| 563 | Masons, tilers, and carpet installers | 135 | 4.44 | -0.1136 | 0.0167 |
| 567 | Carpenters | 2,635 | 2.28 | -0.0737 | 0.0556 |
| 573 | Drywall installers | 40 | 10 | -0.0774 | 0.0054 |
| 575 | Electricians | 6,252 | 2.38 | 0.0745 | 0.0262 |
| 577 | Electric power installers | 9,727 | 1.12 | 0.1850 | 0.0457 |
| 579 | Painters, construction and maintenance | 1,925 | 5.51 | -0.1776 | 0.0951 |
| 583 | Paperhangers | 10 | 10 | 0.0458 | -0.0049 |
| 585 | Plumbers, pipe fitter | 3,589 | 2.06 | -0.0085 | 0.0337 |
| 593 | Insulation workers | 405 | 40.25 | -0.1998 | -0.0728 |
| 594 | Paving, surfacing, and tamping equipment operators | 11 | 18.18 | -0.0921 | 0.0032 |
| 595 | Roofers and slaters | 32 | 6.25 | 0.0520 | 0.0012 |
| 596 | Sheet metal duct installers | 317 | 1.89 | 0.0618 | -0.0115 |
| 597 | Structural metal work | 80 | 3.75 | -0.0533 | 0.0084 |
| 599 | Construction trades | 121 | 4.96 | -0.2362 | -0.0067 |
| 615 | Explosives workers | 29 | 3.45 | -0.0557 | -0.0028 |
| 628 | Production supervisor | 9,782 | 21.43 | 0.1484 | -0.0136 |
| 637 | Machinists | 1,054 | 3.61 | 0.1185 | 0.0431 |
| 643 | Boilermakers | 171 | 1.75 | 0.0572 | -0.0297 |
| 649 | Engravers | 25 | 16 | 0.0750 | -0.0081 |
| 658 | Furniture and wood finishers | 15 | 6.67 | -0.0739 | -0.0437 |
| 666 | Dressmakers and seams | 98 | 82.65 | -0.2571 | 0.0359 |
| 668 | Upholsterers | 57 | 22.81 | -0.0014 | 0.0064 |
| 669 | Shoe repairers | 8 | 12.5 | -0.3016 | 0.0388 |
| 675 | Hand molders and shapers | 62 | 8.06 | -0.0832 | 0.0481 |
| 677 | Optical goods workers | 1,172 | 79.18 | 0.0152 | 0.0532 |
| 678 | Dental laboratory and medical appliance technicians | 17,335 | 78.76 | -0.0354 | -0.0011 |
| 679 | Bookbinders | 248 | 41.94 | -0.1676 | -0.0136 |

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 686 | Butchers and meat cutters | 57 | 17.54 | -0.1933 | 0.0610 |
| 687 | Bakers | 435 | 58.39 | -0.1815 | -0.0659 |
| 688 | Batch food makers | 30 | 50 | -0.2947 | 0.0332 |
| 694 | Water and sewage treatment plant operators | 1,938 | 4.13 | -0.2794 | 0.0807 |
| 695 | Power plant operators | 4,863 | 6.29 | 0.2244 | 0.0144 |
| 696 | Plant and system operators | 4,135 | 2.25 | 0.1005 | 0.0309 |
| 699 | Other plant and system operators | 764 | 7.46 | 0.0323 | -0.0922 |
| 706 | Punching and stamping press operatives | 72 | 12.5 | -0.2158 | 0.0183 |
| 708 | Drilling and boring machine operators | 9 | 22.22 | -0.1339 | 0.0333 |
| 709 | Grinding, abrading, buffing workers | 33 | 18.18 | -0.0528 | -0.0045 |
| 723 | Metal platers | 10 | 10 | -0.0364 | 0.0142 |
| 726 | Wood lathe, routing, and planning machine operators | 607 | 5.93 | 0.1268 | -0.0035 |
| 727 | Sawing machine operators | 14 | 50 | -0.1953 | 0.0241 |
| 733 | Other woodworking machine operators | 37 | 2.7 | -0.4042 | 0.0015 |
| 734 | Printing machine operators | 414 | 22.71 | -0.1117 | 0.0019 |
| 736 | Typesetters and compositors | 2,983 | 27.02 | -0.0941 | -0.0765 |
| 743 | Textile cutting machine operators | 9 | 22.22 | -0.0740 | 0.0043 |
| 744 | Textile sewing machine operators | 167 | 86.83 | -0.1286 | -0.0584 |
| 745 | Shoemaking machine operators | 4 | 25 | -0.0556 | 0.0157 |
| 747 | Pressing machine operators (clothing) | 103 | 47.57 | -0.2472 | -0.0234 |
| 748 | Laundry workers | 3,797 | 81.12 | -0.3499 | -0.0025 |
| 749 | Miscellaneous textile machine | 45 | 26.67 | -0.1298 | 0.0378 |
| 754 | Packers, fillers, and wrappers | 188 | 56.38 | -0.3470 | 0.0070 |
| 755 | Extruding and forming machine operators | 61 | 19.67 | -0.2264 | 0.0001 |
| 756 | Mixing and blending machine operatives | 135 | 22.96 | -0.2230 | -0.0298 |
| 757 | Separating, filtering | 161 | 26.71 | 0.0138 | 0.0272 |
| 759 | Painting machine operators | 345 | 9.28 | -0.0853 | 0.0201 |
| 764 | Washing, cleaning, and pickling machine operators | 27 | 37.04 | -0.0789 | 0.0001 |
| 765 | Paper folding machine operators | 69 | 33.33 | -0.3476 | 0.0328 |
| 766 | Furnace, kiln, and oven operators | 171 | 57.31 | -0.1518 | -0.0237 |
| 769 | Slicing and cutting machine operators | 124 | 24.19 | -0.3102 | 0.0004 |
| 773 | Motion picture projectionists | 231 | 14.72 | -0.3908 | 0.1155 |
| 774 | Photographic process | 1,015 | 48.37 | -0.0461 | 0.0198 |
| 779 | Machine operators | 5,257 | 29.1 | -0.1621 | -0.0213 |
| 783 | Welders and metal cut | 2,413 | 2.32 | 0.0827 | 0.0730 |
| 785 | Assemblers of electric equipment | 1,680 | 40.48 | -0.3256 | -0.0416 |
| 799 | Graders and sorters in manufacturing | 5,411 | 33.54 | 0.0133 | 0.0672 |
| 803 | Supervisors of motor vehicle transportation | 8,523 | 18.2 | 0.0471 | -0.0554 |
| 804 | Truck, delivery, and tractor drivers | 89,990 | 3.83 | -0.1798 | -0.0731 |
| 808 | Bus drivers | 10,636 | 34.23 | -0.3329 | 0.0228 |
| 809 | Taxi cab drivers and chauffeurs | 8,379 | 15.5 | -0.5859 | 0.1579 |
| 813 | Parking lot attendant | 2,076 | 12.14 | -0.4132 | -0.0164 |
| 823 | Railroad conductors and yardmasters | 4,238 | 3.92 | 0.2275 | -0.0266 |
| 824 | Locomotive operators | 5,307 | 2.68 | 0.2735 | -0.0487 |
| 825 | Railroad brake, couplers | 489 | 1.84 | 0.2348 | -0.0319 |
| 829 | Ship crews and marine engineers | 2,320 | 3.32 | 0.0359 | 0.0256 |
| 844 | Operating engineers of construction equipment | 1,278 | 2.58 | 0.1045 | 0.0087 |

| Occupation code | Occupation title | Total observation | Female percentage | Random Intercept | Random slope |
|---|---|---|---|---|---|
| 848 | Crane, derrick, winch and hoist operators | 496 | 2.42 | 0.2040 | 0.0005 |
| 853 | Excavating and loading machine operators | 236 | 2.12 | -0.0656 | 0.0330 |
| 859 | Miscellaneous material moving occupations | 477 | 3.56 | 0.0976 | 0.0005 |
| 865 | Helpers, construction | 103 | 12.62 | -0.2142 | 0.0531 |
| 866 | Helpers, surveyors | 108 | 4.63 | -0.2949 | 0.0503 |
| 869 | Construction laborers | 1,957 | 3.37 | -0.1519 | -0.0055 |
| 874 | Production helpers | 194 | 25.77 | -0.2012 | 0.0253 |
| 875 | Garbage and recyclable material collectors | 213 | 13.62 | -0.4718 | -0.0254 |
| 878 | Machine feeders and offbearers | 128 | 45.31 | -0.1624 | 0.0172 |
| 883 | Freight, stock, and material handlers | 940 | 10.32 | -0.1791 | 0.0802 |
| 885 | Garage and service station related occupations | 219 | 9.13 | -0.2974 | 0.0221 |
| 887 | Vehicle washers and equipment cleaners | 1,256 | 27.79 | -0.3463 | -0.0137 |
| 888 | Packers and packagers | 1,592 | 54.46 | -0.4743 | -0.0964 |
| 889 | Laborers outside construction | 14,880 | 10.36 | -0.1978 | -0.0016 |

***Appendix F. Compare nonprofit random intercept model and random slope model***

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Df | 2 | 20.000 | 2.828 | 18 | 19 | 21 | 22 |
| AIC | 2 | 4,071,958.000 | 8,523.939 | 4,065,931.000 | 4,068,945.000 | 4,074,972.000 | 4,077,986.000 |
| BIC | 2 | 4,072,217.000 | 8,487.397 | 4,066,215.000 | 4,069,216.000 | 4,075,217.000 | 4,078,218.000 |
| logLik | 2 | -2,035,959.000 | 4,264.798 | -2,038,975.000 | -2,037,467.000 | -2,034,451.000 | -2,032,943.000 |
| deviance | 2 | 4,071,918.000 | 8,529.596 | 4,065,887.000 | 4,068,903.000 | 4,074,934.000 | 4,077,950.000 |
| Chisq | 1 | 12,062.670 | | 12,062.670 | 12,062.670 | 12,062.670 | 12,062.670 |
| Chi Df | 1 | 4.000 | | 4.000 | 4.000 | 4.000 | 4.000 |
| Pr(> Chisq) | 1 | 0.000 | | 0.000 | 0.000 | 0.000 | 0.000 |

*Notes:*

Model 1:

lmer(lnincwage ~ 1 + fpsctxt100 + FEMctxt100 + nonprofitC + female + edyrsC + latinoC + blackC + asianC + othraceC + speakengC + expC + expsq100th + hourwkC + (1 |Industry) + (1 |Occupation) + (1|State), acs38, REML = FALSE

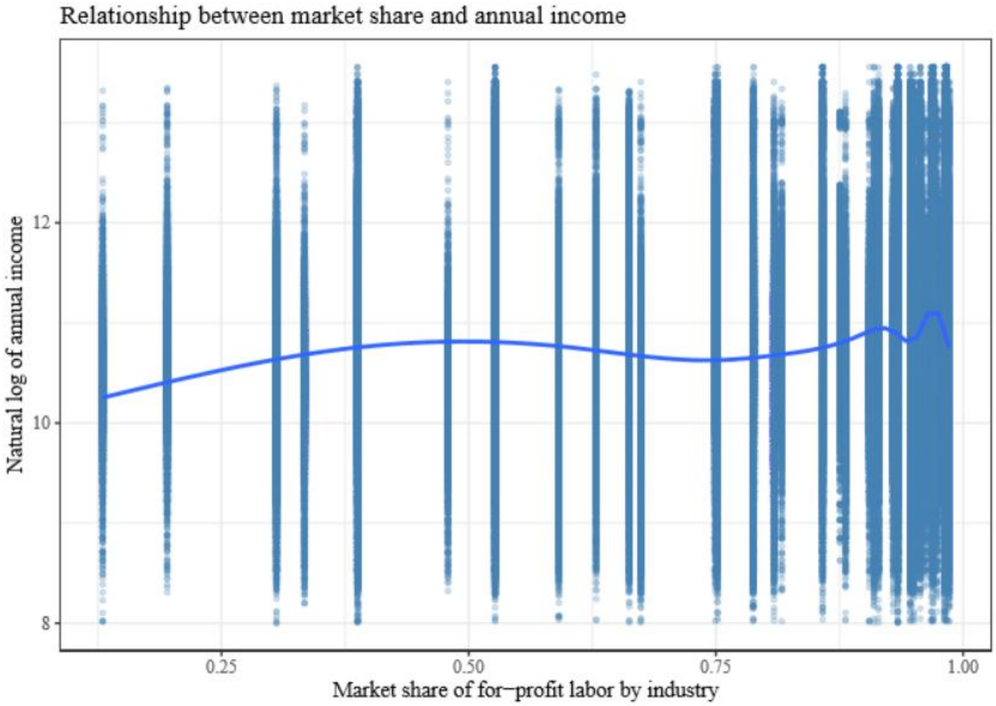
Model 2:

lmer(lnincwage ~ 1 + fpsctxt100 + FEMctxt100 + nonprofitC + female + edyrsC + latinoC + blackC + asianC + othraceC + speakengC + expC + expsq100th + hourwkC + (1 + nonprofitC | Industry) + (1 + nonprofitC | Occupation) + (1 | State), acs38, REML = FALSE)

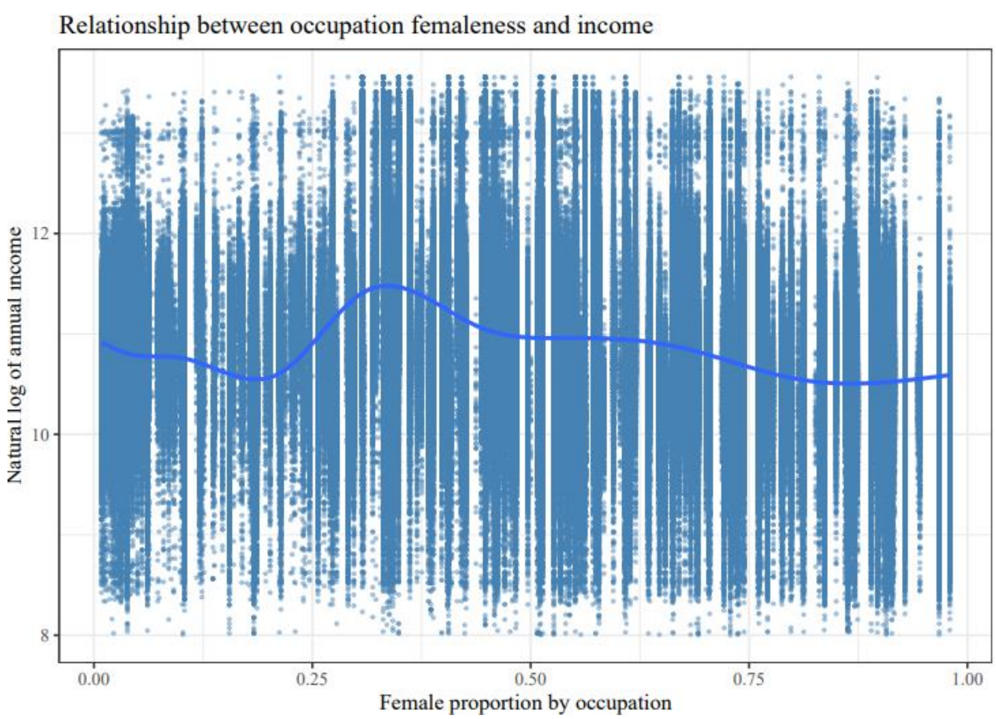
## *Appendix G. Compare estimates with fewer industries*

| | Natural log of annual income | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Fixed Coef. | Random Coef. | FC | RC | FC | RC | FC | RC |
| # of industries | 9 industries (fps<60%) | | 18 industries (fps<86%) | | 20 industries (fps>86%) | | 38 industries (all) | |
| NP workers | 462,628 (53.4%) | | 598,462 (41.6%) | | 66,184 (4.2%) | | 664,646 (22%) | |
| fpsctxt100 | 0.002 | -0.0001 | 0.004*** | 0.003** | 0.005 | 0.005 | 0.004*** | 0.003*** |
| | (0.724) | (-0.073) | (2.708) | (2.279) | (0.552) | (0.520) | (4.213) | (3.537) |
| FEMctxt100 | -0.001*** | -0.001*** | -0.002*** | -0.002*** | -0.001 | -0.001 | -0.001 | -0.001 |
| | (-2.810) | (-2.687) | (-3.487) | (-3.283) | (-1.216) | (-1.604) | (-1.521) | (-1.445) |
| **nonprofitC** | **0.044*****| **-0.010** | **0.015***** | **-0.033**** | **-0.060***** | **-0.072***** | **0.002***** | **-0.057***** |
| | **(45.489)** | **(-0.534)** | **(18.892)** | **(-2.003)** | **(-29.393)** | **(-3.490)** | **(2.891)** | **(-3.893)** |
| femaleC | -0.130*** | -0.129*** | -0.146*** | -0.143*** | -0.215*** | -0.214*** | -0.187*** | -0.185*** |
| | (-114.615) | (-114.212) | (-157.099) | (-154.280) | (-220.014) | (-219.354) | (-276.068) | (-272.933) |
| edyrsC | 0.076*** | 0.076*** | 0.075*** | 0.075*** | 0.071*** | 0.071*** | 0.073*** | 0.073*** |
| | (279.299) | (277.932) | (353.433) | (352.352) | (313.692) | (314.045) | (469.262) | (468.674) |
| latinoC | -0.014*** | -0.013*** | -0.041*** | -0.040*** | -0.081*** | -0.080*** | -0.065*** | -0.063*** |
| | (-7.113) | (-6.993) | (-27.438) | (-26.398) | (-50.839) | (-50.502) | (-58.414) | (-57.061) |
| blackC | -0.040*** | -0.039*** | -0.057*** | -0.055*** | -0.125*** | -0.125*** | -0.095*** | -0.093*** |
| | (-24.621) | (-24.224) | (-44.663) | (-43.418) | (-77.460) | (-77.372) | (-92.220) | (-90.402) |
| asianC | -0.014*** | -0.014*** | -0.018*** | -0.018*** | -0.037*** | -0.037*** | -0.030*** | -0.029*** |
| | (-6.519) | (-6.684) | (-10.335) | (-10.614) | (-18.154) | (-18.129) | (-22.173) | (-21.799) |
| othraceC | -0.040*** | -0.040*** | -0.051*** | -0.050*** | -0.075*** | -0.074*** | -0.067*** | -0.066*** |
| | (-11.519) | (-11.522) | (-18.799) | (-18.549) | (-25.328) | (-25.135) | (-32.827) | (-32.353) |
| speakengC | 0.040*** | 0.041*** | 0.049*** | 0.048*** | 0.046*** | 0.045*** | 0.046*** | 0.045*** |
| | (20.779) | (21.034) | (33.577) | (32.903) | (31.971) | (31.859) | (44.993) | (44.654) |
| expC | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.012*** | 0.012*** | 0.011*** | 0.011*** |
| | (244.435) | (244.407) | (313.477) | (313.746) | (328.158) | (328.734) | (448.690) | (449.153) |
| expsq100th | -0.046*** | -0.046*** | -0.047*** | -0.047*** | -0.059*** | -0.059*** | -0.053*** | -0.053*** |
| | (-139.894) | (-139.922) | (-176.207) | (-175.689) | (-201.457) | (-201.632) | (-267.026) | (-266.867) |
| hourwkC | 0.007*** | 0.007*** | 0.009*** | 0.009*** | 0.016*** | 0.016*** | 0.013*** | 0.013*** |
| | (103.794) | (102.999) | (174.085) | (172.046) | (296.607) | (295.467) | (345.041) | (342.442) |
| Constant | 10.545*** | 10.547*** | 10.624*** | 10.617*** | 10.740*** | 10.740*** | 10.682*** | 10.673*** |
| | (249.057) | (250.547) | (301.279) | (311.415) | (281.886) | (281.843) | (368.277) | (374.288) |
| Observations | 866,255 | 866,255 | 1,437,120 | 1,437,120 | 1,579,990 | 1,579,990 | 3,017,110 | 3,017,110 |
| Akaike Inf. Crit. | 954,819 | 952,669 | 1,701,295 | 1,693,066 | 2,313,073 | 2,310,106 | 4,078,169 | 4,066,108 |
| Bayesian Inf. Crit. | 955,029 | 952,925. | 1,701,514 | 1,693,334 | 2,313,294 | 2,310,376 | 4,078,401 | 4,066,393 |
| *Note:* | | | | | | | | *p**p***p<0.01 |

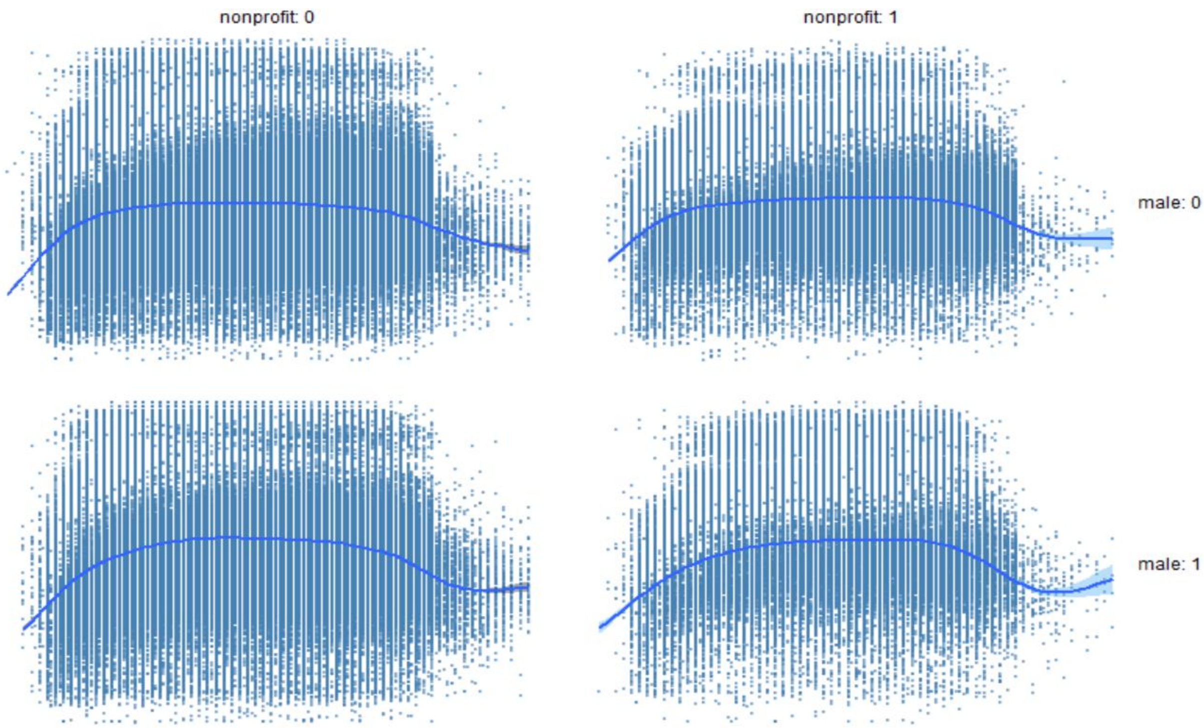
*Appendix H. Linearity check of for-profit share of workers and annual income*




*Appendix I. Linearity check of female percentage and annual income*



*Appendix J. The quadratic relationship between work experience and annual income*



## Bibliography


Addison, J. T., Ozturk, O. D., & Wang, S. (2018). The occupational feminization of wages. *ILR Review*, *71*(1), 208–241. https://doi.org/10.1177/0019793917708314

Adloff, F. (2016). Approaching philanthropy from a social theory perspective. In T. Jung, S. D. Phillips, & J. Harrow (Eds.), *The Routledge Companion to Philanthropy* (pp. 56–71). London: Routledge.

Aguinis, H., Gottfredson, R. K., & Culpepper, S. A. (2013). Best-practice recommendations for estimating cross-level interaction effects using multilevel modeling. In *Journal of Management* (Vol. 39). https://doi.org/10.1177/0149206313478188

Akerlof, G. A. (1984). Gift exchange and efficiency-wage theory: Four views. *The American Economic Review*, *74*(2), 79–83.

Allen, S. G. (1995). Updated notes on the interindustry wage structure, 1890-1990. *Industrial and Labor Relations Review*, *48*(2), 305–321.

*America's Nonprofit Sector* - *Impact*. (2016). Retrieved from https://independentsector.org/resource/americas-nonprofit-sector-impact/

*America's Nonprofit Sector* - *Revenues*. (2016). Retrieved from https://independentsector.org/resource/americas-charitable-sector-revenue/

American Community Survey Design and Methodology. (2009). In *U.S. Census Bureau*. Retrieved from http://www.census.gov/acs/www/Downloads/survey_methodology/acs_design_methodology.pdf

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-Glow giving. *The Economic Journal*, *100*(401), 464–477.

Bania, N., & Leete, L. (2018). The valuation of volunteer labor. In B. A. Seaman & D. R. Young (Eds.), *Handbook of Research on Nonprofit Economics and Management* (Second Edi, pp. 323–336). https://doi.org/10.4337/9781785363528

Barman, E. (2017). The social bases of philanthropy. *Ssrn*. https://doi.org/10.1146/annurev-soc-060116-053524

Bates, D., Maechler, M., Bolker, B., Walker, S., Christensen, R. H. B., Singmann, H., … Fox, J. (2018). *Package "lme4."*

Bell, A., & Jones, K. (2015). Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data. *Political Science Research and Methods*, *3*(1), 133–153. https://doi.org/10.1017/psrm.2014.7

Ben-Ner, A., & Hoomissen, T. Van. (1992). An empirical investigation of the joint determination of the size of the for-profit, nonprofit and government sectors. *Annals of Public and Cooperative Economy*, *63*(3), 391–415.

Ben-Ner, A., Ren, T., & Paulson, D. F. (2011). A sectoral comparison of wage levels and wage inequality in human services industries. *Nonprofit and Voluntary Sector Quarterly*, *40*(4), 608–633. https://doi.org/10.1177/0899764010365012

Benz, M. (2005). Not for the profit, but for the satisfaction? - Evidence on worker well-being in non-profit firms. *Kyklos*, *58*(2), 155–176. https://doi.org/10.1111/j.0023-5962.2005.00283.x

Benz, M., & Frey, B. S. (2008). Being independent is a great thing: Subjective evaluations of selfemployment and hierarchy. *Economica*, *75*(298), 362–383. https://doi.org/10.1111/j.1468-0335.2007.00594.x

Beretvas, S. N. (2008a). Cross-classified and multiple- membership models. In *Handbook of Advanced Multilevel Analysis* (pp. 313–334).

Beretvas, S. N. (2008b). Cross-classified random effects models. *Multilevel Modeling of Educational Data, Pages 161-197*, 161–197.

Biggs, A., & Richwine, J. (2014). *Overpaid or underpaid? A state by state ranking of public employee compensation*. Retrieved from http://www.aei.org/publication/overpaid-or-underpaid-a-state-by-state-ranking-of-public-employee-compensation/

Bishow, J. L., & Monaco, K. A. (2016). Nonprofit pay and benefits: estimates from the National Compensation Survey. *Monthly Labor Review*, (January).

Bliese, P. D., & Hanges, P. J. (2004). Being both too liberal and too conservative: The perils of treating grouped data as though they were independent. *Organizational Research Methods*, *7*(4), 400–417. https://doi.org/10.1177/1094428104268542

Bollinger, C. R., Hirsch, B. T., Hokayem, C. M., & Ziliak, J. P. (n.d.). Trouble in the tails? Earnings non-response and response bias across the distribution. *Journal of Political Economy*.

Boris, E. T., & Steuerle, C. E. (2017). *Nonprofits and government: Collaboration and conflict* (3rd ed.). Washington, D. C.: Urban Institute Press.

Borjas, G. J. (2007). Compensating wage differentials. In *Labor Economics* (4th ed.). Boston: McGraw Hill.

Borjas, G. J., Frech, H. E., & Ginsburg, P. B. (1983). Property rights and wages: The case of nursing homes. *The Journal of Human Resources*, *18*(2), 231–246.

Brown, C., & Medoff, J. (1989). *The employer size wage effect* (No. 2870). Cambridge, MA.

Brown, E., & Slivinski, A. (2018). Markets with competition between for-profit and nonprofit firms. In B. A. Seaman & D. R. Young (Eds.), *Handbook of Research on Nonprofit Economics and Management* (2nd ed.). Cheltenham, UK: Edward Elgar.

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods and Research*, *33*(2), 261–304. https://doi.org/10.1177/0049124104268644

Byrne, P. F. (2014). Do workers profit from the nonprofit tax exemption? The impact of state tax exemption on the nonprofit wage differential of hospital workers. *Public Finance Review*, *42*(2), 199–221. https://doi.org/10.1177/1091142113505678

Callen, J. L., Klein, A., & Tinkelman, D. (2003). Board composition, committees, and organizational efficiency: The case of nonprofits. *Nonprofit and Voluntary Sector Quarterly*, *32*(4), 493–520. https://doi.org/10.1177/0899764003257462

Carman, J. G. (2011). What you don't know can hurt your community: Lessons from a local United Way. *Nonprofit Management & Leadership*, *21*(4), 433–448. https://doi.org/10.1002/nml

Cassar, L., & Meier, S. (2018). Nonmonetary incentives and the implications of work as a source of meaning. *Journal of Economic Perspectives*, *32*(3), 215–238. https://doi.org/10.1257/jep.32.3.215

Chang, C. F., & Tuckman, H. P. (1996). The goods produced by nonprofit organizations. *Public Finance*

*Quarterly*, *24*(1), 25–43.

Child, C. (2010). Whither the turn? The ambiguous nature of nonprofits' commercial revenue. *Social Forces*, *89*(1), 145-145–162. https://doi.org/10.1353/sof.2010.0058

Cordes, J. J., & Weisbrod, B. A. (1998). Differential taxation of nonprofits and the commercialization of nonprofit revenues. *Journal of Policy Analysis and Management*, *17*(2), 195–214. https://doi.org/10.1002/(SICI)1520-6688(199821)17:2<195::AID-PAM5>3.0.CO;2-C

Cortis, N. (2017). Access to philanthropic and commercial income among nonprofit community service organisations. *Voluntas*, *28*(2), 798–821. https://doi.org/10.1007/s11266-016-9715-2

de Ruijter, J. M. P., & Huffman, M. L. (2003). Gender composition effects in the Netherlands: A multilevel analysis of occupational wage inequality. *Social Science Research*, *32*(2), 312–334. https://doi.org/10.1016/S0049-089X(02)00061-3

Deaton, A. (2010). Instruments, randomization, and learning about development. *Journal of Economic Literature*, *48*(2), 424–455. https://doi.org/10.1257/jel.48.2.424

Diez Roux, A. V. (2002). A glossary for multilevel analysis. *Journal of Epidemiology and Community Health*, *56*(8), 588–594. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12118049%0Ahttp://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC1732212

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, Vol. 48, pp. 147–160. https://doi.org/10.2307/2095101

Ehrenberg, R. G., & Smith, R. S. (2018). Compensating wage differentials and labor markets. In *Modern Labor Economics Theory and Public Policy* (13th ed.). New York and London: Routledge.

Eikenberry, A. M., & Kluver, J. D. (2004). The marketization of the nonprofit sector: Civil society at risk? *Public Administration Review*, *64*(2), 132–140. https://doi.org/10.1111/j.1540-6210.2004.00355.x

Elster, J. (2011). The Valmont effect: The warm-glow theory of philanthropy. In P. Illingworth, T. Pogge, & L. Wenar (Eds.), *Giving Well: The Ethics of Philanthropy*. Oxford and New York: Oxford University Press.

Enders, C. K., & Tofighi, D. (2007). Centering Predictor Variables in Cross-Sectional Multilevel Models: A New Look at an Old Issue. *Psychological Methods*, *12*(2), 121–138. https://doi.org/10.1037/1082-989X.12.2.121

Evren, Ö., & Minardi, S. (2017). Warm-glow giving and freedom to be selfish. *The Economic Journal*, *127*(603), 1381–1409. https://doi.org/10.1111/ecoj.12351

Faulk, L., Edwards, L. H., Lewis, G. B., & McGinnis, J. (2012). An analysis of gender pay disparity in the nonprofit sector: An outcome of labor motivation or gendered jobs? *Nonprofit and Voluntary Sector Quarterly*, *42*(6), 1268–1287. https://doi.org/10.1177/0899764012455951

Fields, J., & Wolff, E. N. (1995). Interindustry wage differentials and the gender wage gap. *ILR Review*, *49*(1), 105–120.

Fischer, R. L., Wilsker, A., & Young, D. R. (2011). Exploring the revenue mix of nonprofit organizations: Does it relate to publicness? *Nonprofit and Voluntary Sector Quarterly*, *40*(4), 662–681. https://doi.org/10.1177/0899764010363921

Forbes, D. P., & Kirsch, D. A. (2011). The study of emerging industries: Recognizing and responding to some central problems. *Journal of Business Venturing*, *26*(5), 589–602. https://doi.org/10.1016/j.jbusvent.2010.01.004

Foster, W., & Bradach, J. (2005). Should non-profits profits seek profits? *Harvard Business Review*, (February), 92–100.

Frank, R. H. (1996). What price the moral high ground? *Southern Economic Journals*, *63*(1), 1–17.

Friedland, R., Alford, R. R., & Robert R. Alford. (1991). Bringing society back in: Symbols, practices and institutional contradictions. In W. W. Powell & P. J. DiMaggio (Eds.), *The New Institutionalism in Organizational Analysis* (pp. 232–263). Chicago: The University of Chicago Press.

Froelich, K. A. (1999). Diversification of revenue strategies: Evolving dependence in nonprofit organizations. *Nonprofit and Voluntary Sector Quarterly*, *28*(3), 246–268. Retrieved from http://nvs.sagepub.com/content/28/3/246.full.pdf+html

Frumkin, P. (2002). *On Being Nonprofit: A conceptual and policy primer*. Harvard University Press.

Frumkin, P., & Andre-Clark, A. (1999). Nonprofit compensation and the market. *University of Hawaii Law Review*, *21*, 425–485. https://doi.org/10.3366/ajicl.2011.0005

Frumkin, P., & Andre-Clark, A. (2000). When missions, markets, and politics collide: Values and strategy in the nonprofit human services. *Nonprofit and Voluntary Sector Quarterly*, *29*(1), 141–163. https://doi.org/10.1177/089976400773746373

Frumkin, P., & Keating, E. K. (2010). The price of doing good: Executive compensation in nonprofit organizations. *Policy and Society*, *29*(3), 269–282. https://doi.org/10.1016/j.polsoc.2010.07.004

Gibelman, M. (2000). The nonprofit sector and gender discrimination. *Nonprofit Management and Leadership*, *10*(3), 251–269. https://doi.org/10.1002/nml.10303

Glaeser, E. L., & Shleifer, A. (2001). Not-for-profit entrepreneurs. *Journal of Public Economics*, *81*(1), 99–115. https://doi.org/10.1016/S0047-2727(00)00130-4

Grasse, N., Davis, T., & Ihrke, D. (2014). Understanding the compensation of nonprofit executive directors: Examining the influence of performance and organizational characteristics. *Nonprofit Management & Leadership*, *24*(3), 377–398. https://doi.org/10.1002/nml

Grønbjerg, K. A. (2001). The U.S. nonprofit human service sector: A creeping revolution. *Nonprofit and Voluntary Sector Quarterly*, *30*(2), 276–297. https://doi.org/10.1177/0899764001302006

Guo, B. (2006). Charity for profit? Exploring factors associated with the commercialization of human service nonprofits. *Nonprofit and Voluntary Sector Quarterly*, *35*(1), 123–138. https://doi.org/10.1177/0899764005282482

Gupta, N., Conroy, S. A., & Delery, J. E. (2012). The many faces of pay variation. *Human Resource Management Review*, *22*(2), 100–115. https://doi.org/10.1016/j.hrmr.2011.12.001

Hager, M. A. (2003). Current practices in allocation of fundraising expenditures. *New Directions for Philanthropic Fundraising*, *2003*(41), 39–52. https://doi.org/10.1002/pf.40

Haisken-Denew, J. P., & Schmidt, C. M. (1991). Interindustry and interregion differentials: Mechanics and interpretation. *The Review of Economics and Statistics*, *3*(1984).

Hallock, K. F. (2000). Compensation in nonprofit organizations. *Research in Personnel and Human Resources Management*, *19*, 243–294. https://doi.org/doi:10.1016/S0742-7301(00)19007-3

Hallock, K. F. (2002). *The gender pay and employment gaps for top managers in US nonprofits*. Retrieved from http://digitalcommons.ilr.cornell.edu/workingpapers/93/

Hamann, D. J., & Ren, T. (2013). Wage inequality and performance in nonprofit and for-profit organizations. *Nonprofit Management & Leadership*, *24*(2), 207–228. https://doi.org/10.1002/nml

Handy, F., & Katz, E. (1998). The wage differential between nonprofit institutions and corporations: Getting more by paying less? *Journal of Comparative Economics*, *26*(2), 246–261. https://doi.org/10.1006/jcec.1998.1520

Handy, F., Mook, L., Ginieniewicz, J., & Quarter, J. (2007). The moral high ground: Perceptions of wage differentials among executive directors of Canadian nonprofits. *The Philanthropist*, *21*(2), 109–127.

Hansmann, H. B. (1980). The role of nonprofit enterprise. *The Yale Law Journal*, *89*(5), 835–901. https://doi.org/10.4324/9781315184555-12

Hansmann, H. B. (1987). The effect of tax exemption and other factors on the market share of nonprofit versus for-profit firms. *National Tax Journal*, *XL*, 71–82.

Hatfield, E., Rapson, R. L., & Bensman, L. (2012). Equity Theory. *Encyclopedia of Human Behavior*, 73–78. https://doi.org/10.1016/B978-0-12-375000-6.00153-1

Hirsch, B. T. (2005). Why do part-time workers earn less? The role of worker and job skills. *ILR Review*, *58*(4), 525–551. Retrieved from https://www.jstor.org/stable/pdf/30038605.pdf?refreqid=excelsior%3Afeb3836f9a0bb83d5ad5770e74079669

Hirsch, B. T., Macpherson, D. A., & Preston, A. E. (2018). Nonprofit wages: Theory and evidence. In B. A. Seaman & D. R. Young (Eds.), *Handbook of Research on Nonprofit Economics and Management*. Edward Elgar.

Hlavac, M. (2018). *Stargazer: Well-formatted regression and summary statistics tables. R package version 5.2.2*. Retrieved from https://cran.r-project.org/package=stargazer

Hofmann, D. A., & Gavin, M. B. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management*, *24*(5), 623–641. https://doi.org/10.1177/014920639802400504

Holtmann, A. G., & Idson, T. L. (1993). Wage determination of registered nurses in proprietary and nonprofit nursing homes. *The Journal of Human Resources*, *28*(1), 55. https://doi.org/10.2307/146088

Hox, J. J. (2010). *Multilevel Analysis : Techniques and Applications* (2nd ed.). New York and Hove: Routledge.

Hox, J. J., & Maas, C. J. M. (2005). Multilevel Analysis. *Encyclopedia of Social Measurement*, *2*.

Hwang, H., & Powell, W. W. (2009). The rationalization of charity: The influences of professionalism in the nonprofit sector. *Administrative Science Quarterly*, *54*(2), 268–298.

Ito, T., & Domian, D. (1987). A musical note on the efficiency wage hypothesis: Programmings, Wages and Budgets of American Symphony Orchestras. *Economics Letters*, *25*(1), 95–99. https://doi.org/10.1016/0165-1765(87)90022-X

Jaccard, J., & Turrisi, R. (2003). *Interaction Effects in Multiple Regression* (2nd ed.). Thousand Oaks, CA: SAGE Publications Inc.

Jacobson, M. F., & Mazur, L. A. (1995). *Marketing Madness: A Survival Guide for a Consumer Society*. Boulder. San Francisco. Oxford: Westview Press.

Jacoby, W. G. (2000). Loess: a nonparametric, graphical tool for depicting relationships between variables. *Electoral Studies*, *19*, 577–613. https://doi.org/10.1002/wics.104

James, E. (1998). Commercialism among nonprofits: Objectives, opportunities, and constraints. In B. A. Weisbrod (Ed.), *To Profit or Not to Profit: the commercial transformation of the nonprofit sector*. Cambridge, UK: Cambridge University Press.

Jones, D. B. (2015). The supply and demand of motivated labor: When should we expect to see nonprofit wage gaps? *Labour Economics*, *32*, 1–14. https://doi.org/10.1016/j.labeco.2014.11.001

Kerlin, J. A., & Pollak, T. H. (2011). Nonprofit commercial revenue: A replacement for declining government grants and private contributions? *American Review of Public Administration*, *41*(6), 686–704. https://doi.org/10.1177/0275074010387293

Kim, M., & Charbonneau, É. (2018). Caught between volunteerism and professionalism: Support by nonprofit leaders for the donative labor hypothesis. *Review of Public Personnel Administration*, 0734371X1881613. https://doi.org/10.1177/0734371X18816139

King, C., & Lewis, G. B. (2017). Nonprofit pay in a competitive market: Wage penalty or premium? *Nonprofit and Voluntary Sector Quarterly*, *46*(5), 1073–1091. https://doi.org/10.1177/0899764017718633

Kreft, I., & Leeuw, J. de. (1998). *Introducing Multilevel Modeling*. London and New Delhi: SAGE Publications Ltd.

Kreft, I., Leeuw, J. de, & Aiken, L. S. (1995). The effect of different forms of centering in hierarchical linear models. *Multivariate Behavioral Research*, *30*(1), 1–21. https://doi.org/10.1207/s15327906mbr3001

Kreps, D. M. . (1997). Intrinsic motivation and extrinsic incentives source. *American Economic Association*, *87*(2), 359–364.

Krishnan, R., Yetman, M. H., & Yetman, R. J. (2006). Expense misreporting in nonprofit organizations. *Accounting Review*, *81*(2), 399–420. https://doi.org/10.2308/accr.2006.81.2.399

Krueger, A. B., & Summers, L. H. (1988). Efficiency wages and the inter-industry wage structure. *Econometrica*, *56*(2), 259–293.

Kruse, D. (1992). Supervision, working conditions, and the employer size-wage effect. *Industrial Relations*, *31*(2), 229–249.

Lanfranchi, J., & Narcy, M. (2015). Female overrepresentation in public and nonprofit sector jobs: evidence from a French national survey. *Nonprofit and Voluntary Sector Quarterly*, *44*(1), 47–74. https://doi.org/10.1177/0899764013502579

Lecy, J. D., & Searing, E. A. M. (2015). Anatomy of the nonprofit starvation cycle: An analysis of falling overhead ratios in the nonprofit sector. *Nonprofit and Voluntary Sector Quarterly*, *44*(3), 539–563.

Leete, L. (2000). Wage equity and employee motivation in nonprofit and for-profit organizations. *Journal of Economic Behavior & Organization*, *43*, 423–446. https://doi.org/10.1016/S0167-2681(00)00129-3

Leete, L. (2001). Whither the nonprofit wage differential? Estimates from the 1990 Census. *Journal of Labor Economics*, *19*(1), 136–170. https://doi.org/10.1086/209982

Leete, L. (2006). Work in the nonprofit sector. In W. W. Powell & R. Steinberg (Eds.), *The Nonprofit Sector: A Research Handbook* (2nd ed., pp. 159–179). New Haven & London: Yale University Press.

Leroux, A. J. (2019). Student mobility in multilevel growth modeling: A multiple membership piecewise growth model. *Journal of Experimental Education*, *87*(3), 430–448. https://doi.org/10.1080/00220973.2018.1465384

Lewis, G. B. (2010). Modeling nonprofit employment: Why do so many lesbians and gay men work for nonprofit organizations? *Administration and Society*, *42*(6), 720–748. https://doi.org/10.1177/0095399710377434

Lewis, G. B. (2018). Diversity, pay equity, and pay in social work and other professions. *Affilia: Journal of Women and Social Work*, 1–14. https://doi.org/10.1177/0886109917747615

Lewis, G. B., & Frank, S. A. (2002). Who wants to work for government? *Public Administration Review*, *62*, 395–404. https://doi.org/10.1111/0033-3352.00193

Lewis, G. B., & Ng, E. S. (2013). Sexual orientation, work values, pay, and preference for public and nonprofit employment: Evidence from Canadian postsecondary students. *Canadian Public Administration*, *56*(4), 542–564. https://doi.org/10.1111/capa.12039

Lundström, T. (2001). Child protection, voluntary organizations, and the public sector in Sweden. *Voluntas*, *12*(4), 355–371. https://doi.org/10.1023/A:1013970632035

Macpherson, D. A., & Hirsch, B. T. (1995). Wages and gender composition: Why do women's jobs pay less ? *Journal of Labor Economics*, *13*(3), 426–471.

Maier, F., Meyer, M., & Steinbereithner, M. (2016). Nonprofit organizations becoming business-like: A systematic review. *Nonprofit and Voluntary Sector Quarterly*, *45*(1), 1–23. https://doi.org/10.1177/0899764014561796

Mas, A., & Pallais, A. (2016). *Valuing alternative work arrangements* (No. 22708). Retrieved from http://www.nber.org/papers/w22708

McCoach, D. B. (2010). Hierarchical linear modeling. In G. R. Hancock & R. O. Mueller (Eds.), *The Reviewer's Guide to Quantitative Methods in the Social Sciences* (pp. 1–21). Retrieved from https://mycourses.purdue.edu/bbcswebdav/pid-860231-dt-content-rid-2776283_1/courses/wl_59257.201310/ENE595_HLM.pdf

McKeever, B. (2018). The Nonprofit Sector in Brief 2018. Retrieved May 20, 2019, from https://nccs.urban.org/publication/nonprofit-sector-brief-2018#the-nonprofit-sector-in-brief-2018-public-charites-giving-and-volunteering

McKeever, B., & Gaddy, M. (2017). The Nonprofit Workforce: By the Numbers. Retrieved March 1, 2018, from https://nonprofitquarterly.org/2016/10/24/nonprofit-workforce-numbers/

Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology*, *83*(2), 340–363.

Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy*, *66*(4), 281–302.

Mirvis, P. H., & Hackett, E. J. (1983). Work and work force characteristics in the nonprofit sector. *Monthly Labor Review*, (April).

Mocan, H. N., & Tekin, E. (2003). Nonprofit sector and part-time work: An analysis of employer–

employee matched data on child care workers. *The Review of Economics and Statistics*, *85*(1), 38–50.

Moerbeek, M. (2004). The consequence of ignoring a level of nesting in multilevel analysis. *Multivariate Behavioral Research*, *39*(1), 129–149. https://doi.org/10.1207/s15327906mbr3901

Onyx, J., & Maclean, M. (1996). Careers in the third sector. *Nonprofit Management and Leadership*, *6*(4), 331–345. https://doi.org/10.1002/nml.4130060404

Oster, S. M. (1998). Executive Compensation in the Nonprofit Sector. *Nonprofit Management & Leadership*, *8*(3), 207–222.

Pfeffer, J., & Langton, N. (1993). The effect of wage dispersion on satisfaction, productivity, and working collaboratively: Evidence from college and university faculty. *Administrative Science Quarterly*, *38*(3), 382–407.

Pfeffer, J., & Salancik, G. R. (1978). The design and management of externally controlled organizations. In (???) H. & R. (Ed.), *The External Control of Organizations: A Resource Dependence Perspective* (pp. 146-).

Piliavin, J. A., & Charng, H. (1990). Altruism: A review of recent theory and research. *Annual Review of Sociology*, *16*(1990), 27–65. https://doi.org/10.1006/mthe.2000.0222

Powell, W. W., & Owen-Smith, J. (1998). Universities as creators and retailers of intellectual property: Life-sciences research and commercial development. In B. A. Weisbrod (Ed.), *To Profit or Not to Profit: the commercial transformation of the nonprofit sector* (p. 340). Cambridge, UK: Cambridge University Press.

Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics*, *31*(4), 437–448. https://doi.org/10.3102/10769986031004437

Preston, A. E. (1988). The effects of property rights on labor costs of nonprofit firms: An application to the day care industry. *Journal of Labour Economics*, *36*(March), 337–350.

Preston, A. E. (1989). The nonprofit worker in a for-profit world. *Journal of Labor Economics*, *7*(4), 438–463.

Preston, A. E. (1990a). Changing labor market patterns in the nonprofit and for-profit sectors: Implications for nonprofit management. *Nonprofit Management & Leadership*, *1*(1).

Preston, A. E. (1990b). Women in the white-collar nonprofit sector: The best option or the only option? *The Review of Economics and Statistics*, *72*(4), 560–568.

Preston, A. E., & Sacks, D. W. (2010). Nonprofit wages: Theory and evidence. In B. A. Seaman & D. R. Young (Eds.), *Handbook of Research on Nonprofit Economics and Management*. Cheltenham, UK: Edward Elgar.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods* (2nd ed.). Thousand Oaks, London, New Dehli: SAGE Publications Inc.

Roberts, J. K., & Bates, D. (2010). *Cross-Classified Models in the Context of Value-Added Background to Value-Added Modeling*. 1–14.

Roomkin, M. J., & Weisbrod, B. A. (1999). Managerial compensation and incentives in for-profit and nonprofit hospitals. *Journal of Law Economics & Organization*, *15*(3), 750–781. https://doi.org/10.1093/jleo/15.3.750

Rose-Ackerman, S. (1986). Altruistic nonprofit firms in competitive markets: The case of day-care centers in the United States. *Journal of Consumer Policy*, *9*(3), 291–310. https://doi.org/10.1007/BF00380301

Rose-Ackerman, S. (1996). Altruism, nonprofits, and economic theory. *Journal of Economic Literature*, *34*(2), 701–728.

Ruhm, C. J., & Borkoski, C. (2003). Compensation in the nonprofit sector. *The Journal of Human Resources*, *38*(4), 992–1021.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, ocial development, and well-being. *American Psychologist*, *55*(1), 68–78. https://doi.org/10.1002/jsfa.2740050407

S.Smith, R. (1979). Compensating wage differentials and public policy. *ILR Review*, *32*(3), 339–352. https://doi.org/10.2307/2522263

Salamon, L. M. (1987). Of market failure, voluntary failure, and third-party government: Toward a theory of government-nonprofit relations in the modern welfare state. *Nonprofit and Voluntary Sector Quarterly*, *16*(1–2), 29–49. https://doi.org/10.1177/089976408701600104

Salamon, L. M. (1993). The marketization of welfare: changing nonprofit and for-profit roles in the American Welfare State. *Social Service Review*, *67*(1), 16–39. https://doi.org/10.1086/603963

Salamon, L. M. (1999). The nonprofit sector at a crossroads: The case of America. *Voluntas*, *10*(1), 5–23. https://doi.org/http://dx.doi.org/10.1023/A:1021435602742

Salamon, L. M. (2002). *The tools of government: A guide to the new governance* (L. M. Salamon, Ed.). Oxford and New York: Oxford University Press.

Salamon, L. M. (2015). *The resilient sector revisited* (2nd ed.). Washington, D. C.: Brookings Institution Press.

Salamon, L. M., & Newhouse, C. L. (2019). *The 2019 nonprofit employment report*.

Sampson, S. D., & Moore, L. L. (2008). Is there a glass ceiling for women in development. *Nonprofit Management & Leadership*, *18*(3), 321–339. https://doi.org/10.1002/nml

Seibel, W. (2013). 2.6. Organizational behavior and organizational function: Toward a micro-macro theory of the third sector. *The Third Sector: Comparative Studies of Nonprofit Organizations*, (2013), 107–122.

Smith, D. H., Stebbins, R. A., & Dover, M. A. (2006). *A Dictionary of Nonprofit Terms and Concepts*. Bloomington IN: Indiana University Press.

Snijders, T. A. B. (2005). Fixed and random effects. In *Encyclopedia of Statistics in Behavioral Science.* (Vol. 2, pp. 664–665). https://doi.org/10.1111/j.1541-0420.2010.01463.x

Steinberg, R. (1990). Labor economics and the nonprofit sector: A literature review. *Nonprofit and Voluntary Sector Quarterly*, *19*(2), 151–169. https://doi.org/10.1177/089976409001900206

Thaler, R. H. (1989). Anomalies: Interindustry wage differentials. *Journal of Economic Perspectives*, *3*(2), 181–193. https://doi.org/10.1257/jep.3.2.181

Tinkelman, D., & Neely, D. G. (2018). Revenue interactions: crowding in, crowding out, or neither? In B. A. Seaman & D. R. Young (Eds.), *Handbook of Research on Nonprofit Economics and Management* (2nd ed.). Cheltenham, UK: Edward Elgar.

Tranmer, M., & Steel, D. G. (2001). Ignoring a level in a multilevel model: Evidence from UK census data. *Environment and Planning A*, *33*(5), 941–948. https://doi.org/10.1068/a3317

Tuckman, H. P. (1998). Competition, commercialization, and the evolution of nonprofit organizational structures. In B. A. Weisbrod (Ed.), *To Profit or Not to Profit: the commercial transformation of the nonprofit sector*. Cambridge, UK: Cambridge University Press.

U.S. Census Bureau. (2017). *North American Industry Classification System*. https://doi.org/10.1159/000443915

Van Den Noortgate, W., Opdenakker, M. C., & Onghena, P. (2005). The effects of ignoring a level in multilevel analysis. *School Effectiveness and School Improvement*, *16*(3), 281–303. https://doi.org/10.1080/09243450500114850

Warren, Z. (2008). Occupational employment in the not-for-profit sector. *Monthly Labor Review*, *11*(November), 11–43.

Weisbrod, B. A. (1983). Nonprofit and proprietary sector behavior: Wage differentials among lawyers. *Journal Labor Economics*, *1*(3), 246–263.

Weisbrod, B. A. (1988). *The Nonprofit Economy*. Cambridge, Massachusetts: Harvard University Press.

Weisbrod, B. A. (1998a). Modeling the nonprofit organization as a multiproduct firm: A framework for choice. In B. A. Weisbrod (Ed.), *To Profit or Not to Profit: the commercial transformation of the nonprofit sector*. Cambridge, UK: Cambridge University Press.

Weisbrod, B. A. (1998b). The nonprofit mission and its financing: Growing links between nonprofits and the rest of the economy. In B. A. Weisbrod (Ed.), *To Profit or Not to Profit: the commercial transformation of the nonprofit sector*. Cambridge, UK: Cambridge University Press.

Werner, S., & Gemeinhardt, G. (1995). Nonprofit organizations: What factors determine pay levels? *Compensations and Benefits Review*, *25*(September/ October), 53–60. https://doi.org/10.1177/088636879502700511

Wilsker, A. L., & Young, D. R. (2010). How does program composition affect the revenues of nonprofit organizations?: Investigating a benefits theory of nonprofit finance. *Public Finance Review*, *38*(2), 193–216. https://doi.org/10.1177/1091142110369238

Woltman, H., Feldstain, A., Mackay, J. C., & Rocchi, M. (2012). An introduction to hierarchical linear modeling. *Tutorials in Quantitative Methods for Psychology*, *8*(1), 52–69. https://doi.org/10.2307/2095731

Yan, W., & Sloan, M. F. (2016). The impact of employee compensation and financial performance on nonprofit organization donations. *American Review of Public Administration*. https://doi.org/10.1177/0275074014554000

Yellen, J. L. (1984). Efficiency wage models of unemployment. *Information and Macroeconomics*, *74*(2), 200–205.

Young, D. R. (2017). *Financing Nonprofits and Other Social Enterprises: A Benefits Approach*. Cheltenham, UK: Edward Elgar.

## Vita

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