# The Changing Monopsony Power in Higher Education: Evidence without Instruments

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**Abstract**

This study investigates the dynamics of universities' wage-setting power in a public system located in a "red" state that has undergone major tenure-policy changes. Facing challenges due to the absence of valid instruments and with an endogenous, potentially mismeasured salary variable, we propose a method to estimate monopsony power without instruments while accounting for measurement error in the endogenous regressor. We find substantial wage-setting power, exceeding both the national average and that of a comparable public system in a "blue" state. The estimated monopsony power declined during the policy-change period and rebounded in the COVID period.

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# 1 Introduction

The notion that employers, regardless of size, possess some degree of wage-setting (monopsony) power has received growing recognition in labor economics. Monopsony power has been documented across a wide range of labor markets, including higher education.[1] Emerging evidence shows that public and industrial policies, such as minimum wages (e.g., Azar et al. 2024; Dube, Lester, and Reich 2016), antitrust and merger policy (Azar and Marinescu 2024), and institutional features of the labor market, including pay transparency (Baker et al. 2023) and unionization (e.g., Prager and Schmitt 2021; Benmelech, Bergman, and Kim 2022), can meaningfully shape employers' wage-setting power. More broadly, the political environment may be a fundamental driver of these institutional differences and thus another potentially important determinant.

The growing blue-red state divide has produced significant differences in higher education governance and labor policies across the United States. "Red" states have implemented reforms that alter traditional faculty protections, such as tenure, sparking debates on academic freedom and job security (Anderson 2023; Douglass 2022; Fischer 2022). The impacts of reforms on tenure could be far-reaching, extending beyond academic freedom to the faculty labor market. These reforms are likely to alter the attractiveness and amenities of the faculty profession, influence labor supply, and increase job turnover—all of which could in turn affect universities' ability to set salaries. Despite their prominence in policy debates, it remains unclear whether and how universities' monopsony power responds to such reforms. As similar reforms continue to be proposed in other states, understanding their implications for wage determination and monopsony power is essential.

In this paper, we investigate monopsony power in the labor market for university faculty and how it responds to institutional and political conditions. We consider a public university system that has undergone major tenure-policy changes, namely the University System of Georgia (USG), establishing a novel and comprehensive faculty-level dataset on three research R1 universities

[1] Manning (2021), Ashenfelter et al. (2022), Card (2022), and Kline (2025) provide comprehensive reviews of the existing empirical evidence and the micro-foundations of monopsony.

within the USG. Georgia, among the red states, serves as a prominent example of the aforementioned trend.[2] The data combines administrative salary records with faculty characteristics and publication metrics scraped online, spanning from the pre-policy-change period (2010-2013), the policy-change period (2014-2019), and the COVID period (2020-2022). The estimation of the monopsony power often lies in estimating the wage elasticity of labor supply. In this framework, instrumental variables for the endogenous salary variable are typically required. To overcome the empirical challenges that suitable instruments are not readily available in our setting, we extend the method of Lewbel, Schennach, and Zhang (2024) (hereafter LSZ) and estimate the labor supply elasticity without instruments, simultaneously accounting for endogeneity and measurement error in the endogenous regressor.[3] Exploiting the triangular structure and a different set of covariance information than LSZ, the proposed method achieves identification under minimal assumptions in a more general model with a vector of common unobservables, with measurement error as a special case. GMM estimators are constructed based on low-order moments derived from higher-moment restrictions.

Based on our proposed approach, we examine the USG' wage-setting power and how it evolves across periods associated with tenure-policy changes. Moreover, we compare exploitation rates, a common measure of monopsony power, for the USG with those for a university system in a Democratic-led state. We find substantial wage-setting power in this "red"-state public system, well above both the national average and the "blue"-state benchmark. Monopsony power declines sharply around the policy change and rebounds during the COVID period.

Our paper makes two main contributions. Empirically, we provide novel evidence on monopsony power in a public university system for which the standard separation-based approach is difficult to implement owing to the lack of suitable instruments. We further document differ-

[2]For example, The Washington Post article "*Political polarization is sorting colleges into red and blue schools*" cites Georgia's tenure policy reform as an example of the red-blue divide in higher education between Democrat-led and Republican-led states (Anderson 2023). Similar views are documented by Douglass (2022): "*In Georgia, and despite widespread faculty protest, Republican Governor Brian Kemp appointed former two-term governor Sonny Perdue to lead the 26-institution University of Georgia system; its governing board then made it easier to fire tenured professors*". Likewise, Fischer (2022) notes, "*There is a partisan geography to higher ed's current clashes. ..., recent high-profile controversies over such issues as mask mandates, critical race theory, and tenure have occurred in states where Republicans control the governor's office, the state legislature, or both*".

[3]Section 2.1 provides a detailed discussion of our empirical model and the identification challenges we face.

ences in monopsony power across universities in red and blue states and analyze the evolution of monopsony power over time within the studied university system. Our analysis highlights how monopsony power responds to academic reforms and macroeconomic shocks, offering new insights into the dynamics of faculty labor markets. In doing so, we complement recent work on monopsony in academia (Goolsbee and Syverson 2023; Yu and Flores-Lagunes 2024) and enrich the broader empirical literature on monopsony power across various contexts (see Kline 2025; Sokolova and Sorensen 2021; Manning 2021; Ashenfelter et al. 2022; Card 2022, for comprehensive reviews). Additionally, our findings suggest that academic reforms, including tenure policy changes, influence not only job security, academic freedom, and productivity, as commonly discussed, but also universities' monopsony power, highlighting a labor market channel through which such reforms affect compensation. Accordingly, this paper contributes to the literature on the consequences of academic reforms (see, for example, Quach and Yu 2025; Nieddu, Nisticò, and Pandolfi 2025; Ehrenberg, Pieper, and Willis 1998; Checchi, De Fraja, and Verzillo 2021) by providing new evidence from ongoing reforms in the United States that are evolving across states and attracting considerable policy attention.

Methodologically, we propose a new estimator that achieves identification without instruments. Related studies include Rigobon (2003), Klein and Vella (2010), and Lewbel (2012) which use heteroskedasticity as a source of identification, imposing restrictions on how the variance, covariance, or higher moments of errors depend on the regressors. Our approach allows for either heteroskedasticity or homoskedasticity. Research on using higher moments to identify error-in-variable models (Cragg 1997; Dagenais and Dagenais 1997) can be viewed as a special case of our framework, with specific restrictions on model parameters. In particular, they omit the crucial element of endogeneity arising from a common unobserved variable. As a result, our identification approach is not a direct extension of these studies and requires different techniques. There is also a body of literature addressing both endogeneity and measurement error in nonlinear models or models with a binary endogenous regressor (e.g., Song, Schennach, and White 2015; Hu, Shiu, and Woutersen 2015; Ura 2018). These studies typically rely on repeated measurements or instruments (or conditional variables) to address both issues. We focus on empirical settings where such auxiliary information is unavailable. The proposed approach is well suited to settings with mismeasured endogenous variables and can be readily applied to a broad class of empirical problems beyond higher education.

**The Conceptual Model** The idea of firms' monopsony (wage-setting) power dated back to Robinson (1933), who first documented that geographical isolation, workers' idiosyncratic preferences, and information frictions can result in market failures and an upward-sloping labor supply curve to the firm, giving them power to exert influence upon the wage paid to workers. Since then, this idea has been further developed by labor economists. In theory, an employer can acquire monopsony power from several sources.[4] Regardless of its sources, the extent of monopsony power depends on the wage elasticity of labor supply faced by the employer: a monopsonist employer faces an upward-sloping labor supply curve and, as a result, pays a wage below the marginal revenue product of labor. To see this, consider that an employer optimally chooses the employment level ($N$) to minimize the total labor cost, given the revenue-maximizing level of production. The cost minimization problem can be written as:

$$\min_N w(N)N, \; s.t. \; Y(N) = \bar{Y} \tag{1}$$

where $w(N)$ denotes the wage level and $Y(N)$ represents the production function.[5] Solving equation (1), we obtain the following key relationship,

$$\frac{\text{MRP} - w}{w} = \frac{1}{\varepsilon} \tag{2}$$

[4]Earlier work, often referred to as "modern" monopsony (see Manning 2021), builds on the search model of Burdett and Mortensen (1998) and hinges on the presence of search frictions. In the seminal paper, Manning (2003) demonstrates that firms can exercise monopsony power despite the presence of many competitors in a frictional labor market. In another strand of research, known as the "new classical" monopsony model, monopsony power arises from workers' idiosyncratic preferences and firm differentiation (e.g., Card et al. 2018; Lamadon, Mogstad, and Setzler 2022). A recent study, Kline (2025), consolidates the two models and shows that employers possess monopsony power under imperfect information and worker heterogeneity in their outside options, where heterogeneity in outside options can arise from search frictions, idiosyncratic preferences, and other factors.

[5]In the context of non-profit-maximizing organizations, one can think of the production function as the production of educational services or faculty members' research output. In other words, rather than aiming to maximize profit, universities may focus on maximizing the value of educational services or the research output produced by faculty, subject to a budget constraint. As a result, public universities encounter a similar resource allocation problem comparable to that of private firms.

Define the rate of exploitation (E), a common index for measuring the extent of monopsony power, as $(MRP - w)/w$. Equation (2) indicates that the exploitation rate is equivalent to the inverse of the wage elasticity of labor supply, $\varepsilon = \frac{\partial N}{\partial w}\frac{w}{N}$ (Ashenfelter et al. 2022). In a perfectly competitive market, as the labor supply is perfectly elastic ($\varepsilon \to \infty$), the employer possesses no monopsony power and pays workers the equivalent of their marginal revenue product (MRP), i.e., $w$ = MRP. Alternatively, if $\varepsilon = 5$, the rate of exploitation rate is 20%, implying that the employer pays workers 80% of their MRP. Moreover, by rearranging equation (2), we can write the optimal wage equation in a markdown format:

$$w = \frac{\varepsilon}{1+\varepsilon} MRP = (1-e)MRP$$

where the wage markdown $e = 1/(1+\varepsilon)$. It is related to the exploitation rate through $e = E/(1+E)$. In this study, to facilitate exposition, we adopt the exploitation rate (E) as the measure of monopsony power.

# 2 Identifying Monopsony Power without Instruments

## 2.1 The Separation-based Approach and Identification Challenges

Given the previous discussion, credibly estimating the wage elasticity of labor supply ($\varepsilon$) and the labor supply curve to the firm becomes the pillar of empirical analyses of monopsony power. Researchers have proposed several estimation strategies to quantify the labor supply elasticity across various empirical settings, with the key hinges on exploiting exogenous variation in wages to address the joint determination of labor demand and labor supply.[6] For example, instrumenting wages in an employment determination equation would identify the labor supply elasticity (Kline 2025). In addition to approaches directly recover $\varepsilon$, researchers can infer the labor supply elasticity from labor market dynamics under a steady-state assumption. Specifically, the canonical model, proposed by Manning (2003), leverages the linear relationship between $\varepsilon$ and the wage elasticity of recruits ($\varepsilon_r$) and the wage elasticity of separation ($\varepsilon_s$) in the steady state, i.e., $\varepsilon = \varepsilon_r - \varepsilon_s$. Under

[6] See Sokolova and Sorensen (2021) for a comprehensive review.

the assumption that in the steady state, one employer's recruits by offering higher wages should be another employer's quits (i.e., $\varepsilon_r = -\varepsilon_s$), one can show that $\varepsilon = -2\varepsilon_s$. Therefore, $\varepsilon$ can be obtained by estimating $\varepsilon_s$.

Formally, for our application, to estimate the wage elasticity of separation to the university ($\varepsilon_s$), we consider the following model:

$$Separation_i = \gamma \ln Salary_i^* + \tau' X_i + \epsilon_i \tag{3}$$

where $Separation_i$ is a dummy indicator which equals unity if faculty member $i$ left the university of employment during the sample period. $\ln Salary_i^*$ denotes the logarithm of salaries. $\epsilon_i$ denotes the error term in the separation equation. $X_i$ represents the controlled covariates including faculty attributes, work experience, educational background, and research ability. These variables are defined and discussed in detail in Section 3. The wage elasticity of separation $\varepsilon_s$ is then estimated as $\gamma$ divided by the sample mean separation rate $\bar{s}$. Once the wage elasticity of separation is obtained, the wage elasticity of labor supply $\varepsilon$ can be readily estimated as $-2$ times the estimated $\varepsilon_s$. This "separation-based" approach is widely employed in the monopsony literature. Prominent examples include Ransom and Oaxaca (2010), Ransom and Sims (2010), Barth and Dale-Olsen (2009), Hirsch, Schank, and Schnabel (2010), Webber (2016), Dube, Giuliano, and Leonard (2019), Bassier, Dube, and Naidu (2021), Sharma (2023), Azar, Berry, and Marinescu (2022), and Dube, Manning, and Naidu (2025).[7]

Although under the separation-based approach, estimating the wage elasticity of labor supply can be reduced to estimating only the wage elasticity of separation, instrumental variable strategies and exogenous variation in wages are still required to credibly identify these elasticity parameters from the separation equation. Wages are widely acknowledged to be endogenous in separation and recruitment equations, as worker ability, preferences for firm-provided amenities, and the distribution of workers' outside option are common determinants of both wages and labor market

[7]Notably, this estimation strategy relies on the steady-state assumption. We argue that this assumption is likely to hold for occupations facing a "thin" labor market, such as university professors. The mobility of these workers tends to be largely within the industry and the probability of a faculty who moves to a university from another university is fairly high. Indeed, in our sample, the vast majority (approximately 90%) of faculty who joined the USG came from other universities, mirroring the proportion of UC faculty departures who moved to other institutions.

transitions. These factors are generally unobserved by researchers, raising concerns about omitted variable bias. A valid instrument should affect wages while be uncorrelated with the separations except through its impact on wages. Such instruments for wages in academia are generally rare and sometimes unavailable. For example, labor economists often use salary scales as instruments for teacher and faculty salaries (e.g., Ransom and Sims 2010; Hendricks 2015; Leigh 2012; Fitzpatrick 2015). Unfortunately, this instrument is not available for institutions with limited transparency in pay determination, where salary scales are not publicly accessible. This is the case for the public university system under consideration of our practice. The lack of valid instruments prevents identification of the separation equation and, consequently, a credible assessment of the university's monopsony power.

Furthermore, a largely ignored issue in the empirical analysis of monopsony power is that the salary variable is likely subject to measurement error, even when using the institutional data. While salary records provide a snapshot of earnings, they do not capture the full picture of take-home income, which may include benefits, allowances, and external research funding. Moreover, specifically to our application in the context of faculty labor market, faculty salaries are measured by the calendar year, whereas the recruitment in academia is typically based on the academic year. Such discrepancy might cause fluctuations in annual salaries during hiring years, which likely introduces measurement error into the salary variable. The presence of measurement error can bias our estimates and lead to imprecisely measured monopsony power.

To incorporate the measurement error into our model, denoting the measurement error as $e_i$. Given the endogenous and mismeasured salary variable, the observed salaries (denoted as $\ln Salary_i$ and is measured in logarithm) can be written as:

$$\ln Salary_i^* = \ln Salary_i - e_i$$

$$\ln Salary_i = \delta' X_i + U_i + V_i + e_i$$

where $U_i$ captures the common factor that simultaneously determines salaries and separations. $V_i$ represents the unobservables that are specific to salaries. The separation equation is then given by:

$$Separation_i = \gamma \ln Salary_i^* + \tau' X_i + \beta U_i + R_i$$

where $R_i$ denotes the error term that only enters the separation equation, i.e., the unobservables specific to the separation variable. It follows directly that the error term $\epsilon_i$ in equation (3) equals $\beta U_i + R_i$. Plugging the observed salary function back into the separation equation, the model becomes:

$$Separation_i = \gamma \ln Salary_i + \tau' X_i + \beta U_i + R_i - \gamma e_i \tag{4}$$

The presence of unobserved factors $U_i$ in both the salary and separation equations signals the endogeneity of the salary variable. Without valid instruments, standard methods cannot identify the salary coefficient. This problem is further compounded by measurement error in the endogenous regressor, which introduces additional bias and complicates identification. In the following section, we show how the method of Lewbel, Schennach, and Zhang (2024) can be extended to identify $\gamma$, and hence the wage elasticity of separation $\varepsilon_s$, without instrumental variables, while accounting for measurement error in the salary variable.

### 2.2 Model Identification and Estimation

To facilitate exposition, we illustrate the method in a general framework rather than using the notation specific to our monopsony case. We start by demonstrating identification. All proofs are in the Appendix D. Consider a baseline triangular structural model

$$Y^* = U + V \tag{5}$$

$$W = \gamma Y^* + \beta U + R, \tag{6}$$

where $U, V, R$ are unobserved errors with unknown distributions. The endogenous variable $Y^*$ is unobserved, and instead, we observe $Y$, where $Y = Y^* + e$. In addition to the assumptions in LSZ that $U$, $V$, and $R$ are mutually independent and have zero mean, we further assume that $e$ is mean zero and is mutually independent of $U$, $V$, and $R$.[8] Substituting out the unobserved $Y^*$ in

[8] In other words, $e$ is a classical measurement error. The mean zero assumption is a standard location normalization, which can be achieved by demeaning $Y$ and $W$. The mutual independence assumption regarding unobservables is made conditional on all observed covariates. That is, we only require, e.g., $U_i$ be independent of the other unobservables, conditional on the rich set of faculty attributes $X_i$.

equations (5) and (6) yields

$$Y = U + V + e \tag{7}$$

$$W = \gamma Y + \beta U - \gamma e + R. \tag{8}$$

Now we have two common unobserved errors in both equations. We show that a set of moment restrictions, different from that used in LSZ, hold without imposing assumptions on the distribution of the measurement error.[9] Substituting (7) into equation (8) gives:

$$W = \gamma V + \alpha U + R, \quad \text{with} \quad \alpha = \gamma + \beta. \tag{9}$$

We establish the identification of $\gamma$ and $\alpha$ under the following assumption.

**Assumption 1.** *The joint distribution of random variables $Y$ and $W$ is observed. The unobserved random variables $U$, $V$, $R$ and $e$ are mean zero and mutually independent.*

Let $\Phi_Y(\zeta) \equiv \ln E(\exp(i\zeta Y))$, $\Phi_W(\xi) \equiv \ln E(\exp(i\xi Y))$ denote the logarithms of marginal characteristic functions (also known as second characteristic functions or cumulant generating functions). Similarly, let $\Phi_{Y,W}(\zeta, \xi) \equiv \ln E(\exp(i\zeta Y + i\xi W))$ represent the log of joint characteristic function. The coefficients of a Maclaurin series expansion of the second characteristic function are cumulants of the distribution. The marginal cumulant of order $j$ is thus defined by $\kappa_Y^j = i^{-j}\Phi_Y^{(j)}(0)$, where $\Phi_Y^{(j)}(0)$ denotes the $j-$th order derivative of $\Phi_Y(\zeta)$ evaluated at $\zeta = 0$ (Lukacs 1970, equation (2.4.2)). Similarly, the joint cumulant of order $(j,l)$ is defined as $\kappa_{Y,W}^{j,l} = i^{-(j+l)}\Phi_{Y,W}^{(j,l)}(0,0)$, where $\Phi_{Y,W}^{(j,l)}(0,0)$ represents the mixed partial derivatives of order $(j,l)$ evaluated at $\zeta = 0$ and $\xi = 0$.

**Theorem 1.** *Let Assumption 1, equations (7) and (9) hold. Define the moment $g_p(\alpha,\gamma) \equiv \kappa_{Y,W}^{1+p,3} - (\gamma+\alpha)\kappa_{Y,W}^{2+p,2} + \alpha\gamma\kappa_{Y,W}^{3+p,1}$. It satisfies the constraint $g_p(\alpha,\gamma) = 0$ for any $p \in \{0,1,\dots\}$. Moreover, let $q, \tilde{q} \in \{0,1,\dots\}$ with $q < \tilde{q}$. Assume $-\infty < \gamma < \alpha < \infty$. If the absolute moment of order $\tilde{q}$ exists for $U$, $V$, $R$ and $e$ and $\kappa_{Y,W}^{3+\tilde{q},1}\kappa_{Y,W}^{2+q,2} - \kappa_{Y,W}^{3+q,1}\kappa_{Y,W}^{2+\tilde{q},2} \neq 0$, then the moment restrictions $g_q(\alpha,\gamma) = 0$ and $g_{\tilde{q}}(\alpha,\gamma) = 0$ point identify the parameters $\alpha$ and $\gamma$, with $\alpha$ being equal to the larger root.*

[9]Note that in the presence of measurement error, moments used for identification in LSZ generally do not hold without imposing additional distributional assumptions. For example, for moment constraint (8) in Lemma 1 in LSZ to hold, it requires $E(e^4) = 0$. In the general identification theorem, for higher-order moment conditions in LSZ to continue holding, all cumulants of $e$ of order greater than two must be zero. However, such distributional assumptions are unlikely to be satisfied in practice (for example, asymmetric measurement errors are explicitly considered in Li and Vuong 1998; Bonhomme and Robin 2010; Dong, Otsu, and Taylor 2022).

Intuitively, the mutual independence assumption allows the joint characteristic function to be expressed as products of marginal characteristic function. This makes it possible to represent joint cumulants across different orders (essentially different mixed covariances) as an additively separable function of the marginal cumulants of unobserved variables of the same orders. The restriction $\kappa_{Y,W}^{3+\tilde{q},1}\kappa_{Y,W}^{2+q,2}-\kappa_{Y,W}^{3+q,1}\kappa_{Y,W}^{2+\tilde{q},2}\neq 0$ serves as a rank condition, relying on higher-order cumulants that do not vanish.[10] Using the relationships between cumulants and moments[11], we can derive low-order moments for constructing GMM estimators.

**Lemma 1.** *Let Assumption 1, equations (7) and (9) hold, then the following two moment constraints hold:*

$$\begin{aligned} &cov[(W-\gamma Y)(W-\alpha Y),YW]= \\ &\qquad E\left(WY-\gamma Y^2\right)E\left(W^2-\alpha YW\right)+E\left(W^2-\gamma YW\right)E\left(WY-\alpha Y^2\right) \end{aligned} \tag{10}$$

$$\begin{aligned} &cov[(W-\gamma Y)(W-\alpha Y),Y^2W]= \\ &\qquad 2E[(W-\gamma Y)Y]E[(W-\alpha Y)YW]+2E[(W-\alpha Y)Y]E[(W-\gamma Y)YW] \\ &\qquad +E(Y^2)E[(W-\gamma Y)(W-\alpha Y)W]+E(YW)E[(W-\gamma Y)(W-\alpha Y)Y] \\ &\qquad +E[(W-\gamma Y)W]E[(W-\alpha Y)Y^2]+E[(W-\alpha Y)W]E[(W-\gamma Y)Y^2]. \end{aligned} \tag{11}$$

*In particular, we can show that equations (10) and (11) are equivalent to the moment constraints*

$$g_0(\alpha,\gamma)=0, \tag{12}$$

$$g_1(\alpha,\gamma)=0. \tag{13}$$

Lemma 1 provides two equations in two unknowns, $\alpha$ and $\gamma$. Assuming $\alpha>\gamma$, the moment restrictions in Lemma 1 allow us to point identify $\alpha$ and $\gamma$.[12]

The baseline model can be extended to incorporate covariates. Here, we derive the moments

[10]One caveat is that when all unobservables are normally distributed, higher-order cumulants provide no additional information for identification. Other near-normal distributions, such as a t-distribution with sufficiently large degrees of freedom, may yield higher-order cumulants that are close to zero.

[11]Expressing cumulants in terms of central moments can be done manually using Faàdi Bruno's formula or with the mathStatica package in Mathematica.

[12]$g_p(\alpha,\gamma)=0$ implies that any number of additional moments can be derived and construct overidentified GMM models. However, in highly overidentified GMM models (where the number of moments greatly exceeds the number of parameters), it may be preferable to utilize a subset of the moments for estimation. Guidance from the literature on moment selection in GMM estimation, such as Andrews and Lu (2001) can be applied. In the empirical application, we use moment restrictions up to $g_2(\alpha,\gamma)=0$ to improve estimation precision. The full expression of this higher moment is provided in Appendix C.3.

required for identification. Assume $X$ is a $K$ vector of covariates. The model with covariates is

$$Y = \delta' X + U + V + e \tag{14}$$

$$W = \gamma Y + \tau' X + \beta U - \gamma e + R \tag{15}$$

where $\delta$ and $\tau$ are vectors of coefficients, which include constant terms. Define $\tilde{Y}$, $\tilde{W}$, $Q$, and $P$ by $\tilde{Y} = Y - \delta' X$, $\tilde{W} = W - (\gamma\delta + \tau)' X$, $Q = W - \gamma Y - \tau' X$, and $P = W - (\gamma + \beta) Y + (\beta\delta - \tau)' X$. We can extend moment conditions in Lemma 1 to incorporate covariates and construct the following moments for GMM estimation:

$$\begin{aligned} 0 &= E[QP(\tilde{Y}\tilde{W} - \mu_{\tilde{y}\tilde{w}})] - E[Q\tilde{Y}]E[P\tilde{W}] - E[Q\tilde{W}]E[P\tilde{Y}], \\ 0 &= E[QP(\tilde{Y}^2\tilde{W} - \mu_{\tilde{y}\tilde{y}\tilde{w}})] - 2E[Q\tilde{Y}]E[P\tilde{Y}\tilde{W}] - 2E[P\tilde{Y}]E[Q\tilde{Y}\tilde{W}] - E[\tilde{Y}^2]E[QP\tilde{W}] - E[\tilde{Y}\tilde{W}]E[QP\tilde{Y}] \\ &\quad - E[Q\tilde{W}]E[P\tilde{Y}^2] - E[P\tilde{W}]E[Q\tilde{Y}^2], \end{aligned}$$

along with $E[\tilde{Y}\tilde{W} - \mu_{\tilde{y}\tilde{w}}] = 0$, $E[\tilde{Y}^2\tilde{W} - \mu_{\tilde{y}\tilde{y}\tilde{w}}] = 0$, $E[QX] = 0$, and $E[\tilde{Y}X] = 0$. Using above equations, the parameters $(\gamma, \beta, \delta, \tau, \mu_{\tilde{y}\tilde{w}}, \mu_{\tilde{y}\tilde{y}\tilde{w}})$ are estimated via a standard GMM estimation approach.[13] Lastly, in Appendix C, we show that for cases where the unknown distributions of latent variables are of interest, they can be point-identified under extra assumptions about the distribution of the measurement error. We also provide in Appendix C.3 overidentifying moments, enabling more precise estimates than those obtained with exact-identifying moments alone.

## 3 Data

To employ our approach and estimate the separation elasticity without instruments, we leverage a unique and comprehensive faculty-level dataset on the public university system of Georgia, focusing on three primary research universities in the USG: University of Georgia, Georgia State University, and Georgia Institute of Technology. The dataset combines 13 years of individual faculty salary records from 2010 to 2022 with faculty demographics, educational backgrounds and professional experience obtained through online searching, and publication metrics scraped from Google Scholar.

[13] Monte Carlo simulations assessing the finite sample performance of our GMM estimators are presented in Appendix C.4.

For the two key variables in the separation equation (4), $Separation_i$ is a binary indicator which equals to one if faculty member $i$ left his/her campus of employment during the sample period. The faculty salary variable $lnSalary_i$ is measured by the logarithm of the average annual salary of faculty member $i$ during his/her employment period at the university from 2010 to 2022. We control for faculty attributes including job title, field of specialization, gender, and citizenship.[14] We further create a set of variables to control for confounding factors related to faculty's educational background and work experience. Lastly, we use the logarithm of H-index and the logarithm of the total number of citations as two measures of research productivity.[15] More details regarding the data construction and variable definitions can be found in the Online Appendix E.

The final dataset used contains 3,002 tenure-track faculty members. Table B.3 summarizes descriptive statistics of the outcome variable $Separation$, the salary variable $lnSalary$, and the covariates previously described. The average annual salary ranges from $38,500 to $877,880, with the mean at $133,472.14. Separation rate is about 0.25. 35% of faculty members are female and 32% are foreign-born. Our sample consists of 47% full professors, 28% associate professors, with the remaining 24% being assistant professors.

## 4 Empirical Results

**Monopsony in the USG** Based on the newly developed approach, we evaluate monopsony power in the academic labor market within a public university system that underwent significant faculty governance reforms during the sample period—the University System of Georgia (USG). We start by estimating equation (4) using the method developed in this paper, comparing with estimates using the simple OLS. We present in Table 1 the results of $\gamma$ and the estimated labor supply elasticity $\varepsilon$, along with the corresponding rate of exploitation (E) for OLS and the proposed

[14]We infer faculty members' field of specialization by their working department or school. The fields are categorized into nine main groups based on the National Survey of Student Engagement (NSSE)'s major field categories. They are Arts & Humanities (including Communications and Media), Biological Sciences, Physical Sciences, Math & Computer Sciences (CS), Social Sciences & Education, Business, Engineering, Social Service Professions, Health Professions, and Others. For citizenship, since we do not directly observe faculty's nationality from our data, we use the country where faculty members received their undergraduate degree as a proxy.

[15]H-index, proposed by Hirsch (2005), is a publication metric that measures the citation impact of the publications. It has been commonly used in academia as an indicator of the productivity of scholars.

estimators. Failing to address the endogeneity and measurement error concerns, the OLS estimates of $\gamma$ are generally small in magnitude, though statistically different from zero. They imply a small labor supply elasticity and hence suggest significant exploitation rates. For example, in our preferred model with a full set of controls, the labor supply elasticity is estimated at only 0.69, predicting an exploitation rate as high as 150%. Accounting for both endogenous salaries and measurement error, the proposed estimator suggests a significantly higher labor supply elasticity, with the estimated $\gamma$ increasing from $-0.08$ to $-0.34$. The labor supply elasticity is estimated at approximately 2.8 in the preferred model, which is about four times larger than that obtained from the simple OLS. This implies an exploitation rate of about 36%, suggesting that faculty members are paid approximately 36% less than their marginal revenue product.

Table 1 provides robust evidence of monopsony power within the University System of Georgia. It is worth noting that the estimated monopsony power among the three USG institutions appears to be significantly higher than the national average and than that of universities in a blue state. For example, based on the IV strategy, Goolsbee and Syverson (2023) find that, on average, the labor supply elasticity for tenure-track faculty in U.S. higher education is about 5—equivalent to an exploitation rate of 20%, while Yu and Flores-Lagunes (2024) find that the exploitation rate for the University of California system is about 7%. Both of these numbers are substantially smaller than the estimated level of monopsony power in the USG.

Such differences may be associated with several factors, including the adoption of different estimation methods, institutional policies, labor union presence and power, and transparency in the compensation determination process. To gauge the extent to which this difference is related to the methodological differences, we conduct a supplementary analysis comparing 2SLS and our estimates using the University of California data from Yu and Flores-Lagunes (2024). The results are summarized in Table 2. Based on the 2SLS estimation, the exploitation rate at the UC system is estimated at 7%. Without IVs, our estimate yields a rate of 13%. Given the same method, the estimated monopsony power is substantially greater for the USG than for the University of California System. Put differently, the methodological differences may not be the primary factors contributing to the differential monopsony power across institutions. Moreover, recent research documents that pay disclosure—a policy aimed at increasing pay transparency—helps reduce pay compression (Mas 2017) and narrow the gender pay gap (Baker et al. 2023; Bennedsen et al. 2022). In line with this literature, our findings indicate that other aspects of transparency in compensation, such as transparent standardized salary scales and compensation policies, might also contribute to reducing pay compression.[16]

Furthermore, we summarize in Appendix F that the observed monopsony power is likely driven by faculty members who are foreign-born, tenured, male, and work in fields with limited outside opportunities beyond academia. These findings align with previous studies (e.g., Goolsbee and Syverson 2023; Yu and Flores-Lagunes 2024) that found monopsony power to be more pronounced among these groups.

Lastly, we compare the results from Lewbel, Schennach, and Zhang (2024), which account only for endogeneity, with those from the proposed method in Appendix Table B.4. All results are based on the preferred model. Column (1) shows that the estimated wage elasticity of labor supply is approximately 6.5, corresponding to an exploitation rate of 15%, compared with 2.8 and an estimated exploitation rate of 36% under our proposed approach. The comparison suggests that without accounting for measurement error in the salary variable, the labor supply elasticities estimated using Lewbel, Schennach, and Zhang (2024) are likely overstated, which in turn leads to an underestimated exploitation rate. In other words, the LSZ estimate may be more biased relative to the true exploitation rate than our estimate. In addition, using the University of California sample, the LSZ estimate implies an exploitation rate of 15%, with the wage elasticity of labor supply estimated at 6.8. Consistent with the above discussion, our estimate is closer to the 2SLS estimate than the LSZ estimate, further suggesting that the proposed estimator is likely less biased. Together, these findings point to the importance of accounting for measurement error.

[16] The influence of institutional patterns and faculty governance policies on monopsony could be a fruitful area for future research.

**The Changing Monopsony Power Over Time** Employer monopsony power is not static and can vary over time. Beyond assessing its overall level, investigating its changing patterns is also meaningful, as this may provide insights into the forces that moderate monopsony power. Examining the evolution of monopsony power over the years, we find a substantial reduction during the policy-changing period from 2014 to 2019. Figure 1 displays our estimates of $\gamma$ and their 95% confidence intervals, along with the estimated corresponding exploitation rates (indicated by bars) for three time periods: 2010-2013, 2014–2019, and post-2019. The exploitation rate declined sharply from approximately 28% in the pre-2014 period to 8% during 2014–2019, before increasing to 24% post-2019.[17] The significant changes in monopsony power observed from 2014 to 2019 align with a period of significant policy adjustments, during which the USG enacted a series of policy revisions tightening tenure requirements and strengthening post-tenure review.[18] While these revisions aimed to increase faculty accountability, they also raised concerns about academic freedom and tenure security, likely contributing to higher faculty separations. As a result, changes in the separation elasticity are likely reflected in the estimated exploitation rate. One way to understand the decline in universities' monopsony power during this period is to consider it through the lens of workers' idiosyncratic preferences for university-provided amenities. Tenure security is an important amenity associated with faculty occupations, and the previously discussed adverse changes in tenure policy tend to significantly reduce the "quality" of amenities provided by universities, thereby reducing their wage-setting power.

The reduction in the university's monopsony power may also be linked to changes in faculty sorting patterns. Volpe (2024) recently shows that labor supply elasticity to a firm can be affected by wage-amenity trade-offs and sorting, with higher-paying and/or more productive firms tending

[17]Although the estimated $\gamma$ for the period from 2014 to 2019 is significantly different from zero, its standard error is much larger than those of the other periods. This may suggest significant variation in the elasticity of separation among different faculty groups in response to policy changes during this period. However, due to the small sample sizes of the subgroups, we find it infeasible to fully explore this hypothesis.

[18]The Board of Regents, which governs, controls, and manages the University System of Georgia and all USG institutions, publishes official policies and policy revisions on its website (https://www.usg.edu/policymanual/policy_revisions/). Policy revisions related to tenure, such as *Tenure Requirements*, *Criteria for Tenure*, and *Post-Tenure Review*, can be found from November 2013, August 2014, October 2016, October 2017, and May 2018. These revisions established clearer, more rigorous performance standards for tenured faculty and set additional for tenured faculty who did not meet the performance expectations outlined in their post-tenure review.

to attract workers who are more responsive to wage changes, which in turn reduces the firms' wage-setting power. Consistent with this prediction, changes in tenure policies during this period likely deterred faculty members who value university-provided amenities more than wages and are therefore less responsive to wage changes. The remaining faculty members may care less about amenities but be more responsive to wage changes, exhibiting higher wage elasticity of labor supply. Such policy-driven sorting of more wage-responsive faculty would reduce universities' monopsony power. This trend of declining monopsony power might have continued with further tenure policy revisions if not for the impact of COVID-19 at the end of 2019, which introduced substantial labor market uncertainty, reduced outside options, and helped universities regain monopsony power under tenure policies that were less favorable to faculty members. As shown in Figure 1, the estimated exploitation rate rebounded following a substantial decline during 2014–2019. Nevertheless, it did not fully return to its pre–policy-change level.

## 5 Conclusion

We investigate the dynamics of universities' wage-setting power in a system that has undergone significant changes in tenure policy. Confronted with an endogenous and potentially mismeasured salary variable, along with the absence of suitable instruments, we extend the method of LSZ to estimate universities' monopsony power without instrument while accounting for measurement error in the endogenous regressor. Our results shed new light on how monopsony power varies across universities in states with conservative versus liberal governing coalitions and on how ongoing academic reforms shape universities' wage-setting power.

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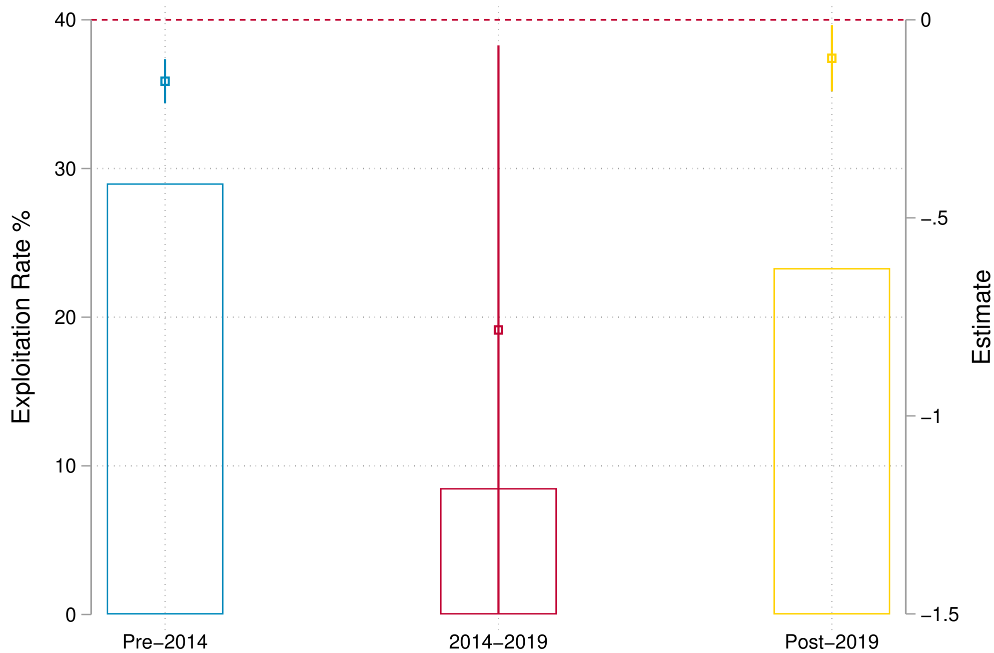



Figure 1: The Changing Monopsony Power

Notes: This figure plots the estimates of $\gamma$ and their 95% confidence intervals based on robust standard errors and using the proposed method. Each bar represents the corresponding exploitation rate (in %), calculated as the inverse of labor supply elasticity. The estimated labor supply elasticities are 3.45, 11.8, 4.3 for the pre-2014, 2014-2019, and post-2019 periods, respectively.

Table 1: Main Results

| | OLS<br>(1) | The Proposed Estimator<br>(2) |
|---|---|---|
| $\gamma$ | -0.084*** | -0.338** |
| | (0.0090) | (0.1342) |
| Labor Supply Elasticity | 0.687 | 2.753 |
| Exploitation Rate | 1.455 | 0.363 |

Notes: Robust standard errors in parentheses. * p < 0.10, **p < 0.05, *** p < 0.01. $N = 3002$. This table summarizes the results of $\gamma$, and the estimated labor supply elasticity $\varepsilon$, along with the corresponding rate of exploitation (E) for the OLS (in Column 1) and the proposed estimator (in Column 2) estimators. The model controls for gender, research ability, years since graduation, and indicators for field, title, university, and citizenship, along with educational and experience controls.

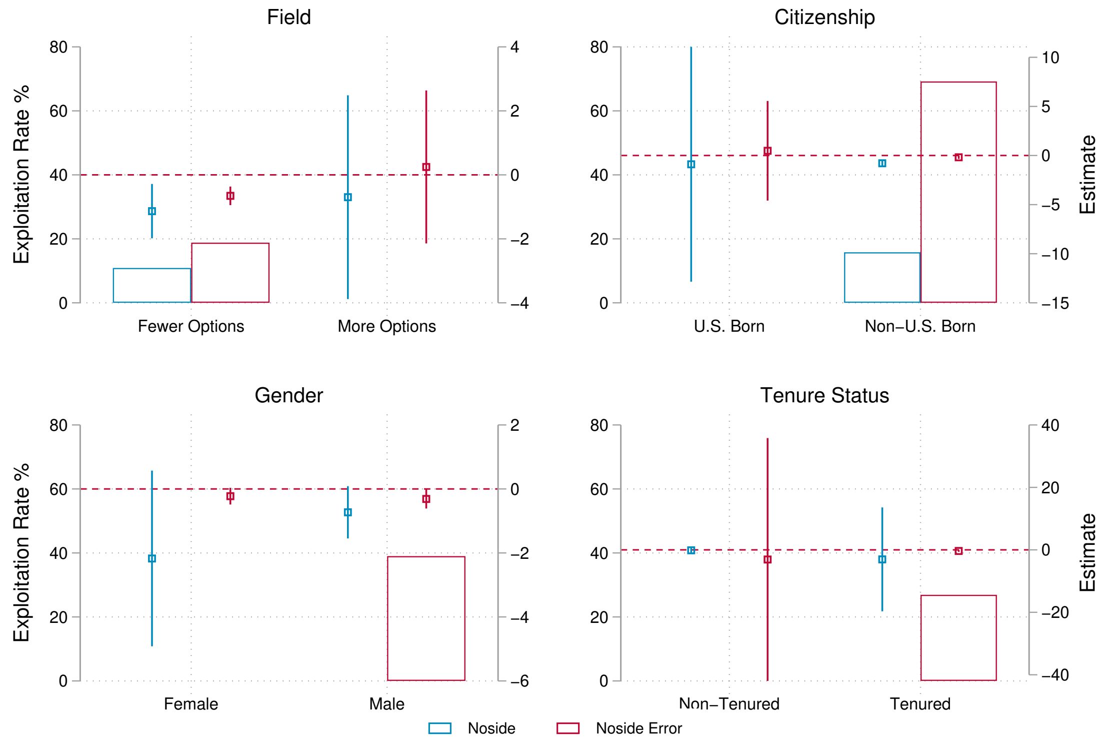
Table 2: Results from the University of California: Comparing 2SLS and the Proposed Estimator

| | 2SLS<br>(1) | The Proposed Estimator<br>(2) |
|---|---|---|
| $\beta$ | -0.760***<br>(0.0805) | |
| $\gamma$ | | -0.395***<br>(0.0652) |
| Labor Supply Elasticity | 15.144 | 7.865 |
| Exploitation Rate | 0.066 | 0.127 |

Notes: Standard errors in parentheses. * p < 0.10, **p < 0.05, *** p < 0.01. $N = 8089$. This table summarizes the estimation results using data from the University of California system, sourced from Yu and Flores-Lagunes (2024). Column (1) shows the 2SLS estimate ($\beta$), adopting university revenue and salary scales as IVs, and reports the same results as Column (2) of Table 3 in Yu and Flores-Lagunes (2024). Column (2) reports the the proposed estimator ($\gamma$). The estimations are based on the same covariates as in Column (1). In the last two rows, we further report the estimated labor supply elasticity and the computed exploitation rate.

# Online Appendix

## A Appendix Figures




A.1: Monopsony Power Across Groups

Notes: This figure plots the estimates of $\gamma$ and their 90% confidence intervals, based on robust standard errors, using both the LSZ method (shown in blue) and the proposed method (shown in red). Each bar represents the corresponding exploitation rate (in %), calculated as the inverse of labor supply elasticity. Estimates of the exploitation rate are omitted when the estimated $\gamma$ is not statistically significant at conventional levels.

## B Appendix Tables

B.1: Monte Carlo Simulations, $n = 2,000$

| | MEAN | SD | LQ | MED | UQ | RMSE | MAE | MDAE |
|---|---|---|---|---|---|---|---|---|
| Design 1 | | | | | | | | |
| $\gamma$ | 0.88 | 0.68 | 0.41 | 0.93 | 1.38 | 0.69 | 0.54 | 0.49 |
| $\beta$ | 1.16 | 0.67 | 0.74 | 1.09 | 1.63 | 0.69 | 0.53 | 0.44 |
| Design 2 | | | | | | | | |
| $\gamma$ | 1.28 | 0.52 | 1 | 1.36 | 1.65 | 0.59 | 0.47 | 0.46 |
| $\beta$ | 0.8 | 0.58 | 0.47 | 0.76 | 1.01 | 0.61 | 0.44 | 0.34 |
| Design 3 | | | | | | | | |
| $\gamma$ | 0.86 | 0.6 | 0.49 | 0.95 | 1.27 | 0.62 | 0.47 | 0.37 |
| $\beta$ | 1.17 | 0.56 | 0.83 | 1.08 | 1.49 | 0.59 | 0.43 | 0.32 |

Notes: We generate 1,000 replications of three designs, with a sample size of $n = 2,000$. Reported summary statistics are the mean (MEAN), the standard deviation (SD), the 25% quantile (LQ), the median (MED), the 75% quantile (UQ), the root mean squared error (RMSE), the mean absolute error (MAE), and the median absolute error (MDAE).

B.2: Monte Carlo Simulations, $n = 800$

| | MEAN | SD | LQ | MED | UQ | RMSE | MAE | MDAE |
|---|---|---|---|---|---|---|---|---|
| Design 1 | | | | | | | | |
| $\gamma$ | 0.87 | 0.81 | 0.42 | 0.95 | 1.43 | 0.82 | 0.59 | 0.5 |
| $\beta$ | 1.31 | 2.16 | 0.71 | 1.14 | 1.66 | 2.18 | 0.71 | 0.5 |
| Design 2 | | | | | | | | |
| $\gamma$ | 1.29 | 0.53 | 1.02 | 1.39 | 1.66 | 0.6 | 0.48 | 0.46 |
| $\beta$ | 0.86 | 0.87 | 0.39 | 0.78 | 1.01 | 0.88 | 0.53 | 0.37 |
| Design 3 | | | | | | | | |
| $\gamma$ | 0.89 | 0.6 | 0.53 | 0.96 | 1.31 | 0.61 | 0.47 | 0.38 |
| $\beta$ | 1.17 | 0.77 | 0.8 | 1.08 | 1.48 | 0.79 | 0.47 | 0.35 |

Notes: We generate 1,000 replications of three designs, with a sample size of $n = 800$. Reported summary statistics are the mean (MEAN), the standard deviation (SD), the 25% quantile (LQ), the median (MED), the 75% quantile (UQ), the root mean squared error (RMSE), the mean absolute error (MAE), and the median absolute error (MDAE).

B.3: Summary Statistics

| Variable | N | Mean | Std. | Min | Max |
|---|---|---|---|---|---|
| Salary | 4289 | 133472.14 | 61637.43 | 38500 | 877880 |
| lnSalary | 4289 | 11.71 | 0.41 | 11 | 14 |
| Separation | 4289 | 0.25 | 0.43 | 0 | 1 |
| Female | 4289 | 0.35 | 0.48 | 0 | 1 |
| Foreign Born | 4289 | 0.32 | 0.47 | 0 | 1 |
| Title | | | | | |
| Assistant | 4287 | 0.24 | 0.43 | 0 | 1 |
| Associate | 4287 | 0.28 | 0.45 | 0 | 1 |
| Full | 4287 | 0.47 | 0.50 | 0 | 1 |
| Field | | | | | |
| Arts & Humanities | 4289 | 0.16 | 0.36 | 0 | 1 |
| Biological Sciences | 4289 | 0.15 | 0.36 | 0 | 1 |
| Physical Sciences, Math, & CS | 4289 | 0.13 | 0.34 | 0 | 1 |
| Social Sciences & Education | 4289 | 0.20 | 0.40 | 0 | 1 |
| Business | 4289 | 0.12 | 0.33 | 0 | 1 |
| Engineering | 4289 | 0.15 | 0.35 | 0 | 1 |
| Social Service Professions | 4289 | 0.02 | 0.15 | 0 | 1 |
| Health Professions | 4289 | 0.05 | 0.22 | 0 | 1 |
| Others | 4289 | 0.02 | 0.13 | 0 | 1 |
| GPhD | 4289 | 0.07 | 0.26 | 0 | 1 |
| GUndergrad | 4289 | 0.04 | 0.19 | 0 | 1 |
| ForeignPhD | 4289 | 0.10 | 0.30 | 0 | 1 |
| ForeignUndergrad | 4289 | 0.32 | 0.47 | 0 | 1 |
| YrsSinceGrad | 4162 | 20.86 | 10.87 | 0 | 60 |
| AnyPostdoc | 4288 | 0.34 | 0.47 | 0 | 1 |
| YrsPostdoc | 4279 | 1.38 | 2.26 | 0 | 16 |
| EverAdmin | 4289 | 0.15 | 0.35 | 0 | 1 |
| lnHindex | 3042 | 3.07 | 0.77 | 0 | 6 |
| lnCitation | 3042 | 7.73 | 1.54 | 0 | 13 |

Notes: This table reports the summary statistics of the salary, separation, and covariates for the use sample. YrsSinceGrad denotes the number of years since the faculty member graduated from the last degree. AnyPostdoc represents a dummy variable indicating any postdoctoral experience of the faculty member. YrsPostdoc counts the total number of years of the post-doctoral experience. EverAdmin denotes a dummy indicator that equals one if the faculty member ever served as dean, provost, director, or chair of a department. GPhD and GUndergrad flag whether the faculty member is an undergraduate or graduate alumni of the three Georgia universities in our sample. ForeignPhD and ForeignUndergrad signify whether the faculty member obtained Ph.D. or Bachelor's from foreign institutions, respectively. lnHindex and lnCitation denote the logarithm of H-index and the logarithm of the total number of citations, respectively.

B.4: Comparing LSZ and the Proposed Estimator

| | LSZ<br>(1) | The Proposed Estimator<br>(2) |
|---|---|---|
| $\gamma$ | -0.804** | -0.338** |
| | (0.3979) | (0.1342) |
| log($\beta$) | -0.236 | 1.078* |
| | (0.5907) | (0.5940) |
| Labor Supply Elasticity | 6.538 | 2.753 |
| Exploitation Rate | 0.153 | 0.363 |

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $N = 3002$ This table compares the LSZ and the proposed estimators. We report $\gamma$, $log(\beta)$, and the estimated labor supply elasticity $\varepsilon$, along with the corresponding rate of exploitation (E). All results are based on the preferred model, controlling for gender, research ability, years since graduation variables, field, title, university, and citizenship indicators, along with educational and experience controls.

## C Additional Theoretical Results

### C.1 Identification of U, V, R, and e

Theorem 1 and Lemma 1 hold without requiring the distributions of $U$, $V$, $R$ and $e$ to be known. Here, we consider the identification of these distributions, which may be of economic interest themselves. For example, recovering variances of unobservables can help determine how much of the error variance is driven by unobserved common factor $U$ compared to other idiosyncratic terms.

**Corollary 1.** *Let Assumption 1, equations (7) and (9) hold. Assume that $e$ is unobserved with known distribution, $U$, $V$ and $R$ are unobserved with unknown distributions, and the characteristic functions of $U$, $V$ and $R$ are nonvanishing everywhere. If $\alpha$ and $\gamma$ are point identified, then the distributions of $U$, $V$ and $R$ are point identified.*

The proof is provided in the Appendix D. We apply a slight variant of Kotlarski's lemma to the joint distribution of $Y$ and $(W-\alpha)/(\gamma-\alpha)$ to prove identification of the distributions of $U$, $V$ and $R$. However, the independence assumptions required for Kotlarski's identity do not hold due to the presence of $e$ (with different slope coefficients) in both $Y$ and $(W-\alpha)/(\gamma-\alpha)$ equations. Specifically, without additional restrictions, the distributions of the unobservables are not point identified under only Assumption 1.

To retrieve identification of $U$, $V$ and $R$, we impose the extra assumption that the distribution of $e$ is known, allowing us to derive Kotlarski's identity with an additional term. While assuming a known distribution for $e$ may seem restrictive, it can be justified in certain practical contexts. For instance, when the true measure of the regressor is unobserved in the main sample but available in a second sample alongside the contaminated measure, the distribution of $e$ can be estimated from the auxiliary sample.[19] If the measurement errors in both samples share the same distribution, we can estimate the distribution from the auxiliary sample and use it in the main sample to obtain identification of other unobservables.

When using lower moments (10) and (11) to identify the model, the extra assumption on $e$ effectively serves the role of a scale normalization. Specifically, the variance of $e$ can first be normalized to a known constant, after which the variance and skewness of the other unobservables, along with $\alpha$ and $\gamma$, can be estimated.

### C.2 A Vector of Common Latent Variables

We now consider a more general version of the model where the unobservables consist of multiple latent variables. Let $\{U_1 \dots U_K\}$ denote a set of unobservables indexed by $k$. Consider the model

$$Y = \sum_{k=1}^{K} U_k + V, \quad W = \gamma Y + \sum_{k=1}^{K} \beta_k U_k + R,$$

[19] When validation data are available, one can test whether $e$ is symmetric and use this as a specification test to choose between the LSZ estimator and our proposed estimator.

which can be rewritten as

$$Y = \sum_{k=1}^{K} U_k + V, \quad W = \sum_{k=1}^{K} \alpha_k U_k + \gamma V + R. \tag{16}$$

The model of mismeasured endogenous variable in section 2.2 is a special case with $K = 2$, $\alpha_1 = \alpha$ and $\alpha_2 = 0$, or $\beta_2 = -\gamma$. When $\beta_1 = \cdots = \beta_K$, the model reduces to the one considered in LSZ. In other words, assuming a scalar common latent variable is equivalent to assuming that all unobserved common factors affect the outcome variable to the same extent.[20]

This general model is applicable to many empirical settings. For example, Jia, Huang, and Zhao (2024) use LSZ's method to estimate a model relating firms' output to foreign equity investment and note that unobservables can include various factors such as CEO ability, development strategies, innovation, etc.

We now formally state our identification theorem of the general model.

**Assumption 2.** *Assume that the joint distribution of random variables $Y$ and $W$ is observed. The unobserved random variables $U_1, \ldots, U_K$, $V$, and $R$ are mean zero and mutually independent.*

**Theorem 2.** *Let Assumption 2 and model (16) hold. Let*

$$\begin{aligned} &g_p(\alpha_1, \ldots, \alpha_K, \gamma) \\ &\quad \equiv \kappa_{Y,W}^{1+p,3} - \left(\sum_k \alpha_k + \gamma\right) \kappa_{Y,W}^{2+p,2} + \left(\sum_{1 \le m < n \le K} \alpha_m \alpha_n + \gamma \sum_k \alpha\right) \kappa_{Y,W}^{3+p,1} - \prod_k \alpha_k \gamma \kappa_Y^{4+p}. \end{aligned}$$

*For any $p \in \{0, 1, \ldots\}$,*

$$g_p(\alpha_1, \ldots, \alpha_K, \gamma) = 0. \tag{17}$$

*Let $\Theta$ be a bounded set and $\theta \equiv (\alpha_1, \ldots, \alpha_K, \gamma) \in \Theta$. Define a mapping $F(\theta) : \Theta \to F(\Theta)$ such that $F(\theta) \equiv [(g_0(\theta), \ldots, g_K(\theta))']$. Assume that the Jacobian matrix $\partial F(\theta)/\partial \theta'$ has full rank for every $\theta \in \Theta$ and the image $F(\Theta)$ is simply connected. Then $\theta = (\alpha_1, \ldots, \alpha_K, \gamma)$ is globally identified over $\Theta$.*

The proof is provided in the Appendix D. Higher-order relations between cumulants of observed and unobserved variables are used to establish equation (17). These moment constraints are then employed to identify $\{\alpha_1, \ldots, \alpha_K, \gamma\}$ under rank conditions that ensure a unique solution. More specifically, identification is achieved by applying a version of Hadamard's global inverse function theorem. Similar arguments have been used in other studies to establish global identification, such as Chernozhukov and Hansen (2006) and Han and Vytlacil (2017). To see what the assumptions entail, consider the mismeasured endogenous regressor model from the previous section. The full rank Jacobian assumption requires that $\kappa_{Y,W}^{3,1} \kappa_{Y,W}^{3,2} - \kappa_{Y,W}^{4,1} \kappa_{Y,W}^{2,2} \neq 0$ and rules out $\{\theta : \alpha = \gamma\}$ (i.e., $\{\theta : \beta = 0\}$) in the parameter space. The assumption that the space $F(\Theta)$ is simply connected implies that it is path-connected, and any loop within the space can be continuously contracted to a single point without leaving the space. This corresponds to the condition that $-\infty < \gamma < \alpha < \infty$ (or $-\infty < \alpha < \gamma < \infty$) in Theorem 1.

As in Lemma 1, the covariance of product of $W - \gamma Y$ and $W - \alpha_k Y$ terms with $WY^j$ can be used as moments to construct GMM estimators. In practice, the number of unobservables $K$ can

[20]If one instead redefines $\tilde{C} = \sum_k \beta_k U_k$ and $\tilde{U} = \sum_k U_k$, so that the model becomes $Y = \tilde{U} + V$ and $W = \gamma Y + \tilde{C} + R$, note that this is not equivalent to the LSZ setup unless $\tilde{C} = \beta \tilde{U}$.

be specified a priori, guided by the economic model, or chosen in a data-driven manner using cross-validation.

In the general model, even when the coefficients are identified, the distributions of unobservables are generally not point identified given that the number of unknown variables is far greater than the number of observed variables.[21] However, similar to Corollary 1, these distributions can be characterized up to normalizations. To formalize this idea, we apply Theorem 2.2 in Rao (1971) to our framework:

**Corollary 2.** *Let Assumption 2 and model (16) hold. Assume that $(\alpha_1, \ldots, \alpha_K, \gamma)$ are identified, $\alpha_k \neq \alpha_j$ for $k \neq j$ and $\alpha \neq \gamma$, and the characteristic function of $(Y, W)$ is specified and does not vanish anywhere. Let $\phi_{U_k}, f_{U_k}$ be two alternative possible characteristic functions of $U_k$, then $\phi_{U_k}(\xi) = f_{U_k}(\xi)\exp(P_K(\xi))$, where $P_K(\xi)$ is a polynomial in $\xi$ of degree $\leq K$. Similarly, let $\phi_V, f_V$ and $\phi_R, f_R$ be two alternative possible characteristic functions of $V$ and $R$, receptively, then $\phi_V(\xi) = f_V(\xi)\exp(P_K(\xi))$ and $\phi_R(\xi) = f_R(\xi)\exp(P_K(\xi))$.*

## C.3 Over-Identifying Moments

When $p = 2$, the moment in Theorem 1 becomes

$$g_2(\alpha, \gamma) \equiv \kappa^{3,3}_{Y,W} - \alpha^2 \kappa^{5,1}_{Y,W} - (\gamma + \alpha)(\kappa^{4,2}_{Y,W} - \alpha \kappa^{5,1}_{Y,W}),$$

from which we can construct additional moments to identify the model.

From results in Cook (1951), we express the joint cumulants of mean zero variables in moments

$$\begin{aligned}
\kappa^{5,1}_{Y,W} &= E[Y^5W] - 5E[Y^4]E[YW] - 10E[Y^3W]E[Y^2] - 10E[Y^2W]E[W^3] + 30E[YW]E[Y^2]E[Y^2] \\
\kappa^{4,2}_{Y,W} &= E[Y^4W^2] - E[Y^4]E[W^2] - 8E[Y^3W]E[YW] - 4E[Y^3]E[YW^2] - 6E[Y^2W^2]E[Y^2] \\
&\quad - 6E[Y^2W]E[Y^2W] + 6E[Y^2]E[Y^2]E[W^2] + 24E[Y^2]E[YW]E[YW] \\
\kappa^{3,3}_{Y,W} &= E[Y^3W^3] - 3E[Y^3W]E[W^2] - E[Y^3]E[W^3] - 9E[Y^2W^2]E[YW] - 9E[Y^2W]E[YW^2] \\
&\quad - 3E[Y^2]E[YW^3] + 18E[Y^2]E[YW]E[W^2] + 12E[YW]E[YW]E[YW]
\end{aligned}$$

We get the additional moments:

$$\begin{aligned}
0 = E[&Y^3W^3 - 3\mu_{ww}Y^3W - \mu_{www}Y^3 - 9\mu_{yw}Y^2W^2 - 9\mu_{yyw}YW^2 - 3\mu_{yy}YW^3 + 18\mu_{yy}\mu_{yw}W^2 \\
&+ 12\mu_{yw}\mu_{yw}YW - (\alpha+\gamma)(Y^4W^2 - \mu_{ww}Y^4 - 8\mu_{yw}Y^3W - 4\mu_{yww}Y^3 - 6\mu_{yy}Y^2W^2 - 6\mu_{yyw}Y^2W \\
&+ 6\mu_{yy}\mu_{yy}W^2 + 24\mu_{yw}\mu_{yw}Y^2) + \alpha\gamma(Y^5W - 5\mu_{yw}Y^4 - 10\mu_{yy}Y^3W - 10\mu_{yyw}W^3 + 30\mu_{yy}\mu_{yy}YW)]
\end{aligned}$$

and

$$E[W^3 - \mu_{www}] = 0.$$

## C.4 Monte Carlo Simulations

To assess the finite sample performance of our GMM estimators, we generate data from the model of equations (7) and (8) without covariates. All of our designs are chosen to satisfy the rank

[21] As shown in Rao (1971), under the framework of model (16) with known coefficients, the joint distribution of two observed variables $(Y, W)$ can identify the distributions of at most three unobserved variables, up to location.

condition (nonzero higher-order cumulants), so the model is point identified from moments of equations (10) and (11).

The true coefficients are set to $\gamma = \beta = 1$. We generate 1,000 replications of three different designs and focus on a relatively small sample size of $n = 800$. In design 1, $U$ and $e$ are log normal while $V$ and $R$ are uniform. We then change the uniform distribution to Gumbel, making $U$ log normal while $V$, $R$, and $e$ Gumbel in design 2, and making $U$ and $e$ log normal while $V$ and $R$ Gumbel in design 3.

Table B.2 reports results from designs 1 to 3, respectively. We report estimates of $\gamma$ and $\beta$. For each parameter, we provide the mean (MEAN), the standard deviation (SD), the 25% quantile (LQ), the median (MED), the 75% quantile (UQ), the root mean squared error (RMSE), the mean absolute error (MAE), and the median absolute error (MDAE).

Across all designs, the primary parameter of interest, $\gamma$ tends to be estimated reasonably precisely: RMSEs range from approximately 0.6 to 0.8 and MAEs from 0.4 to 0.6. $\beta$ is generally less precisely estimated, with relatively larger RMSEs. In Appendix Table B.1, the RMSEs of $\beta$ decrease as the sample size increases to $n = 2,000$. The designs where the unobservables are non-uniform tend to yield more accurate estimates than other designs. Overall, our Monte Carlo results suggest that our estimator performs reasonably well in finite samples.[22]

[22]Millimet (2015) examines the finite sample performance implications of reducing the measurement error (i.e. increasing the reliability ratio) for an endogenous covariate. The reliability ratios calculated following Millimet (2015) for our three designs are 0.64, 0.67, and 0.66, respectively. Table B.2 indicates a negative association between the reliability ratio and the RMSEs. However, in Table B.1, when the sample size increases to $n = 2,000$, the three designs perform similarly.

# D Proofs

*Proof of Theorem 1.* The joint characteristics function of $(Y,W)$ can be represented by

$$\begin{aligned}\phi_{Y,W}(\zeta,\xi) &= E\left[\exp(i\zeta(U+V+e))\exp(i\xi(\alpha U+\gamma V+R))\right]\\ &= E\left[\exp(i(\zeta+\alpha\xi)U)\right]E\left[\exp(i(\zeta+\gamma\xi)V)\right]E\left[\exp(i\xi R)\right]E[\exp(i\zeta e)]\\ &= \phi_U(\zeta+\alpha\xi)\phi_V(\zeta+\gamma\xi)\phi_R(\xi)\phi_e(\zeta),\end{aligned}$$

where the second equality follows because $U,V,R$ and $e$ are mutually independent. The cumulant generating function can be written as

$$\Phi_{Y,W}(\zeta,\xi) = \Phi_U(\zeta+\alpha\xi)+\Phi_V(\zeta+\gamma\xi)+\Phi_R(\xi)+\Phi_e(\zeta).$$

Then for any $p\in\mathbb{N}$ and $0\leq l<3+p$, we have the following relationship

$$\begin{aligned}\kappa_{Y,W}^{3+p-l,l+1} &= \left[\frac{\partial^{3+p+1}\Phi_{Y,W}(\zeta,\xi)}{i^{3+p+1}\partial\zeta^{3+p-l}\partial\xi^{l+1}}\right]_{\zeta=0,\xi=0}\\ &= \alpha^{l+1}\kappa_U^{4+p}+\gamma^{l+1}\kappa_V^{4+p}.\end{aligned}\tag{A.18}$$

Equation (A.18) implies that for $l=0,1,2$, we have the system of equations

$$\begin{aligned}\kappa_{Y,W}^{3+p,1} &= \alpha\kappa_U^{4+p}+\gamma\kappa_V^{4+p},\\ \kappa_{Y,W}^{2+p,2} &= \alpha^2\kappa_U^{4+p}+\gamma^2\kappa_V^{4+p},\\ \kappa_{Y,W}^{1+p,3} &= \alpha^3\kappa_U^{4+p}+\gamma^3\kappa_V^{4+p}.\end{aligned}$$

We can eliminate $\kappa_U^{4+p}$ and $\kappa_V^{4+p}$, and combine the above three equations into a single equation, which gives $g_p(\alpha,\gamma)=0$. Now verifying $g_p(\alpha,\gamma)=0$, we have

$$\begin{aligned}&\kappa_{Y,W}^{1+p,3}-\alpha^2\kappa_{Y,W}^{3+p,1}-(\gamma+\alpha)(\kappa_{Y,W}^{2+p,2}-\alpha\kappa_{Y,W}^{3+p,1})\\ &=\alpha^3\kappa_U^{4+p}+\gamma^3\kappa_V^{4+p}-\alpha^2\left(\alpha\kappa_U^{4+p}+\gamma\kappa_V^{4+p}\right)-(\gamma+\alpha)\left[\left(\alpha^2\kappa_U^{4+p}+\gamma^2\kappa_V^{4+p}\right)-\alpha\left(\alpha\kappa_U^{4+p}+\gamma\kappa_V^{4+p}\right)\right]\\ &=\alpha^3\kappa_U^{4+p}+\gamma^3\kappa_V^{4+p}-\alpha^3\kappa_U^{4+p}-\alpha^2\gamma\kappa_V^{4+p}-(\gamma+\alpha)\left(\gamma^2\kappa_V^{4+p}-\alpha\gamma\kappa_V^{4+p}\right)\\ &=\alpha^3\kappa_U^{4+p}+\gamma^3\kappa_V^{4+p}-\alpha^3\kappa_U^{4+p}-\alpha^2\gamma\kappa_V^{4+p}-\gamma^3\kappa_V^{4+p}-\alpha\gamma^2\kappa_V^{4+p}+\alpha\gamma^2\kappa_V^{4+p}-\alpha^2\gamma\kappa_V^{4+p}\\ &=0,\end{aligned}$$

which is identical to $g_p(\alpha,\gamma)=0$. Now let $q$ and $\tilde{q}$ be two different values of $p$, we have

$$\kappa_{Y,W}^{1+q,3}-\alpha^2\kappa_{Y,W}^{3+q,1}-(\gamma+\alpha)\left(\kappa_{Y,W}^{2+q,2}-\alpha\kappa_{Y,W}^{3+q,1}\right)=0\tag{A.19}$$

$$\kappa_{Y,W}^{1+\tilde{q},3}-\alpha^2\kappa_{Y,W}^{3+\tilde{q},1}-(\gamma+\alpha)\left(\kappa_{Y,W}^{2+\tilde{q},2}-\alpha\kappa_{Y,W}^{3+\tilde{q},1}\right)=0.\tag{A.20}$$

Multiplying (A.19) by $(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1})$ yields

$$\left(\kappa_{Y,W}^{1+q,3} - \alpha^2\kappa_{Y,W}^{3+q,1}\right)\left(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1}\right) - (\gamma+\alpha)\left(\kappa_{Y,W}^{2+q,2} - \alpha\kappa_{Y,W}^{3+q,1}\right)\left(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1}\right) = 0. \quad \text{(A.21)}$$

Replacing $(\gamma+\alpha)(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1})$ with its value from equation (A.20) we obtain a single equation in $\alpha$:

$$-\left(\kappa_{Y,W}^{3+\tilde{q},1}\kappa_{Y,W}^{2+q,2} - \kappa_{Y,W}^{3+q,1}\kappa_{Y,W}^{2+\tilde{q},2}\right)\alpha^2 + \left(\kappa_{Y,W}^{3+\tilde{q},1}\kappa_{Y,W}^{1+q,3} - \kappa_{Y,W}^{3+q,1}\kappa_{Y,W}^{1+\tilde{q},3}\right)\alpha + \left(\kappa_{Y,W}^{1+\tilde{q},3}\kappa_{Y,W}^{2+q,2} - \kappa_{Y,W}^{1+q,3}\kappa_{Y,W}^{2+\tilde{q},2}\right) = 0,$$

which can be rewritten as

$$-F^{3122}\alpha^2 + F^{3113}\alpha + F^{1322} = 0, \quad \text{(A.22)}$$

where $F^{abcd} \equiv \kappa_{Y,W}^{a+\tilde{q},b}\kappa_{Y,W}^{c+q,d} - \kappa_{Y,W}^{a+q,b}\kappa_{Y,W}^{c+\tilde{q},d}$. The roots of equation (A.22) are

$$\alpha_{\pm} = \frac{-F^{3113} \pm \sqrt{F^{3113^2} + 4F^{3122}F^{1322}}}{-2F^{3122}}.$$

The two roots correspond to the value of $\alpha$ and $\gamma$. We require $\kappa_{Y,W}^{3+\tilde{q},1}\kappa_{Y,W}^{2+q,2} - \kappa_{Y,W}^{3+q,1}\kappa_{Y,W}^{2+\tilde{q},2} \neq 0$ to ensure that the denominator $F^{3122}$ is not zero. □

*Proof of Corollary 1.* Denote

$$Z \equiv \frac{W-\alpha Y}{\gamma-\alpha} = V + \frac{1}{\gamma-\alpha}R - \frac{\alpha}{\gamma-\alpha}e.$$

$$\begin{aligned}\phi_{Y,Z}(\zeta,\xi) &= E\left[\exp(i\zeta(U+V+e))\exp\left(i\xi\left(V+\frac{1}{\gamma-\alpha}R-\frac{\alpha}{\gamma-\alpha}e\right)\right)\right] \\ &= \phi_U(\zeta)\phi_V(\zeta+\xi)\phi_R\left(\frac{1}{\gamma-\alpha}\xi\right)\phi_e\left(\zeta-\frac{\alpha}{\gamma-\alpha}\xi\right)\end{aligned} \quad \text{(A.23)}$$

Let $\xi = 0$, we have

$$\phi_{Y,Z}(\zeta,0) = \phi_U(\zeta)\phi_V(\zeta)\phi_e(\zeta). \quad \text{(A.24)}$$

Similarly, let $\zeta = 0$, we have

$$\phi_{Y,Z}(0,\xi) = \phi_V(\xi)\phi_R\left(\frac{1}{\gamma-\alpha}\xi\right)\phi_e\left(-\frac{\alpha}{\gamma-\alpha}\xi\right) \quad \text{(A.25)}$$

Multiplying equations (A.23)-(A.25) yields

$$\phi_{Y,Z}(\zeta,\xi)\phi_V(\zeta)\phi_V(\xi)\phi_e(\zeta)\phi_e\left(-\frac{\alpha}{\gamma-\alpha}\xi\right) = \phi_{Y,Z}(\zeta,0)\phi_{Y,Z}(0,\xi)\phi_V(\zeta+\xi)\phi_e\left(\zeta+\frac{\alpha}{\gamma-\alpha}\xi\right).$$

Let $A(\zeta,\xi) \equiv \phi_e(\zeta)\phi_e\left(-\frac{\alpha}{\gamma-\alpha}\xi\right)/\phi_e\left(\zeta-\frac{\alpha}{\gamma-\alpha}\xi\right)$, and it follows that

$$\phi_V(\zeta+\xi) = \frac{\phi_{Y,Z}(\zeta,\xi)}{\phi_{Y,Z}(\zeta,0)\phi_{Y,Z}(0,\xi)}\phi_V(\zeta)\phi_V(\xi)A(\zeta,\xi).$$

The distribution of $e$ is known by assumption, and $\alpha$ and $\gamma$ are identified. Hence the function $A(\zeta,\xi)$ is known. Additionally, $A(0,\xi)=1$. Recall that $\Phi(\cdot) \equiv \ln\phi(\cdot)$, then

$$\Phi_V(\zeta+\xi) = \ln\frac{\phi_{Y,Z}(\zeta,\xi)}{\phi_{Y,Z}(\zeta,0)\phi_{Y,Z}(0,\xi)} + \Phi_V(\zeta) + \Phi_V(\xi) + \ln A(\zeta,\xi).$$

Then following the steps of proof in Rao (1992), Remarks 2.1.11, it can be shown that

$$\begin{aligned}
\Phi_V(t) &= iE[V]t + \int_0^t \frac{\partial}{\partial\zeta}\left[\ln\frac{\phi_{Y,Z}(\zeta,\xi)}{\phi_{Y,Z}(\zeta,0)\phi_{Y,Z}(0,\xi)}\right]_{\zeta=0} d\xi + \int_0^t \frac{\partial}{\partial\zeta}\left[\ln A(\zeta,\xi)\right]_{\zeta=0} d\xi \\
&= \int_0^t \frac{\partial}{\partial\zeta}\left[\ln\frac{\phi_{Y,Z}(\zeta,\xi)}{\phi_{Y,Z}(\zeta,0)\phi_{Y,Z}(0,\xi)}\right]_{\zeta=0} d\xi + \int_0^t \frac{\partial}{\partial\zeta}\left[\ln A(\zeta,\xi)\right]_{\zeta=0} d\xi
\end{aligned}$$

Using this relationship one can identify the distribution of $V$. Then one can compute the distribution of $U$ and $R$ through

$$\phi_U(\zeta) = \frac{\phi_{Y,Z}(\zeta,0)}{\phi_V(\zeta)\phi_e(\zeta)}, \quad \phi_R\left(\frac{1}{\gamma-\alpha}\xi\right) = \frac{\phi_{Y,Z}(0,\xi)}{\phi_V(\xi)\phi_e(-\alpha/(\gamma-\alpha)\xi)}$$

□

*Proof of Theorem 2.* Under Assumption 2, the cumulant generating function for the general model is

$$\Phi_{Y,W}(\zeta,\xi) = \sum_{i=1}^{K}\Phi_{U_i}(\zeta+\alpha_i\xi) + \Phi_V(\zeta+\gamma\xi) + \Phi_R(\xi).$$

For $\xi=0$ we have

$$\Phi_Y(\zeta) = \sum_{i=1}^{K}\Phi_{U_i}(\zeta) + \Phi_V(\zeta)$$

Then for any $p \in$ and $0 \le l < 3+p$, we have

$$\begin{aligned}
\kappa_{Y,W}^{3+p-l,l+1} &= \left[\frac{\partial^{3+p+1}\Phi_{Y,W}(\zeta,\xi)}{i^{3+p+1}\partial\zeta^{3+p-l}\partial\xi^{l+1}}\right]_{\zeta=0,\xi=0} \\
&= \sum_{i=1}^{K}\alpha_i^{l+1}\kappa_{U_i}^{4+p} + \gamma^{l+1}\kappa_V^{4+p}.
\end{aligned} \tag{A.26}$$

Equation (A.26) implies that

$$\kappa_{Y,W}^{3+p,1} = \sum_{i=1}^{K} \alpha_i \kappa_{U_i}^{4+p} + \gamma \kappa_V^{4+p}, \tag{A.27}$$

$$\kappa_{Y,W}^{2+p,2} = \sum_{i=1}^{K} \alpha_i^2 \kappa_{U_i}^{4+p} + \gamma^2 \kappa_V^{4+p}, \tag{A.28}$$

$$\kappa_{Y,W}^{1+p,3} = \sum_{i=1}^{K} \alpha_i^3 \kappa_{U_i}^{4+p} + \gamma^3 \kappa_V^{4+p}. \tag{A.29}$$

In addition,

$$\kappa_Y^{4+p} = \sum_{i=1}^{K} \kappa_{U_i}^{4+p} + \kappa_V^{4+p} \tag{A.30}$$

Observe that:

$$\begin{aligned}\left(\sum_k \alpha_k + \gamma\right)\left(\sum_{i=1}^{K} \alpha_i^2 \kappa_{U_i}^{4+p} + \gamma^2 \kappa_V^{4+p}\right) &= \sum_{i=1}^{K} \alpha_i^3 \kappa_{U_i}^{4+p} + \gamma^3 \kappa_V^{4+p} \\ &\quad + \left(\sum_{1\le m<n\le K} \alpha_m \alpha_n + \gamma \sum_k \alpha\right)\left(\sum_{i=1}^{K} \alpha_i \kappa_{U_i}^{4+p} + \gamma \kappa_V^{4+p}\right) \\ &\quad - \prod_k \alpha_k \gamma \left(\sum_{i=1}^{K} \kappa_{U_i}^{4+p} + \kappa_V^{4+p}\right).\end{aligned}$$

Therefore, equation (17) can be established using relations (A.27) - (A.30) by eliminating all of $\kappa_{U_i}^{4+p}$ and $\kappa_V^{4+p}$.

A finite set of moment constraints can be constructed from equation (17). Global identification is then obtained through the use of Hadamard-Caccioppoli Theorem (Hadamard (1906) and Caccioppoli (1932)). The theorem states three sufficient conditions for global invertibility: (i) the mapping is proper, (ii) the Jacobian matrix of the mapping has full rank uniformly over the domain, and (iii) codomain of the mapping is simply connected. We first check that $F(\theta)$ is proper: Since $F(\theta)$ is a continuous function, the pre-image of a closed set under $F(\theta)$ is closed. If the domain $\Theta$ is bounded, the pre-image of a bounded set is bounded. Therefore, $F(\theta)$ is proper. The second and third conditions are satisfied by assumptions on the parameter space. □

*Proof of Lemma 1.* **Part 1. Proof of equation (10) and (11).** Define $Q$ and $P$ as $Q = W - \gamma Y = \beta U + R - \gamma e$ and $P = W - \alpha Y = -\beta V + R - \alpha e$. Then the moments are equivalent to

$$\begin{aligned} &cov(QP, YW) - E(QY)E(PW) - E(QW)E(PY) = 0 \quad \text{and} \\ &cov(QP, Y^2W) - 2E(QY)E(PYW) - 2E(PY)E(QYW) - E(Y^2)E(QPW) \\ &\qquad -E(YW)E(QPY) - E(QW)E(PY^2) - E(PW)E(QY^2) = 0. \end{aligned}$$

For the first equation, we have

$$
\begin{aligned}
cov(QP, YW) &= cov[(-\gamma e + \beta U + R)(-\beta V + R - \alpha e), (U + V + e)(\alpha U + \gamma V + R)] \\
&= cov(\gamma\beta e V - \gamma e R - \beta^2 UV + \beta UR - \alpha\beta U e - \beta RV - \alpha e R + \gamma\alpha e^2 + R^2, \\
&\quad \gamma UV + UR + \alpha UV + VR + \alpha e U + \gamma e V + eR + \alpha U^2 + \gamma V^2) \\
&= cov(\gamma\beta e V - \gamma e R - \beta^2 UV + \beta UR - \alpha\beta U e - \beta RV - \alpha e R, \\
&\quad \gamma UV + UR + \alpha UV + VR + \alpha e U + \gamma e V + eR) \\
&= E(\gamma^2\beta e^2 V^2 - \gamma e^2 R^2 - \beta^2\gamma U^2 V^2 + \beta U^2 R^2 - \alpha^2\beta e^2 U^2 - \beta R^2 V^2 - \alpha e^2 R^2 - \alpha\beta^2 U^2 V^2), \\
&= \beta\gamma^2 E(e^2)E(V^2) - \gamma E(e^2)E(R^2) - \beta^2\gamma E(U^2)E(V^2) + \beta E(U^2)E(R^2) \\
&\quad - \alpha^2\beta E(e^2)E(U^2) - \beta E(R^2)E(V^2) - \alpha E(e^2)E(R^2) - \alpha\beta^2 E(U^2)E(V^2),
\end{aligned}
$$

where the equalities follow from Assumption 1. Similarly,

$$
\begin{aligned}
E(QY)E(PW) &= E[(\gamma e + \beta U + R)(U + V + e)]E[(-\beta V + R - \alpha e)(\alpha U + \gamma V + R)] \\
&= E(-\gamma e^2 + \beta U^2)E(\beta\gamma V^2 + R^2) \\
&= \beta\gamma^2 E(e^2)E(V^2) - \gamma E(e^2)E(R^2) - \beta^2\gamma E(U^2)E(V^2) + \beta E(U^2)E(R^2)
\end{aligned}
$$

$$
\begin{aligned}
E(QW)E(PY) &= 2E[(-\gamma e + \beta U + R)(\alpha U + \gamma V + R)]E[(-\beta V + R - \alpha e)(U + V + e)] \\
&= E(\alpha\beta U^2 + R^2)E(-\beta V^2 - \alpha e^2) \\
&= -\alpha\beta^2 E(U^2)E(V^2) - \alpha^2\beta E(U^2)E(e^2) - \beta E(R^2)E(V^2) - \alpha E(e^2)E(R^2),
\end{aligned}
$$

therefore

$$
cov(QP, YW) = E(QY)E(PW) + E(QW)E(PY).
$$

Similarly, we can verify the second equation:

$$
\begin{aligned}
cov(QP, Y^2W) &= cov[(-\gamma e + \beta U + R)(-\beta V + R - \alpha e), (U + V + e)^2(\alpha U + \gamma V + R)] \\
&= cov(\gamma\beta e V - \gamma e R + \gamma\alpha e^2 - \beta^2 UV + \beta UR - \alpha\beta U e - \beta RV + R^2 - \alpha e R, \\
&\quad \alpha U^3 + \alpha U V^2 + \alpha U e^2 + 2\alpha e U^2 + 2\alpha e UV + 2\alpha U^2 V \\
&\quad + \gamma U^2 V + \gamma V^3 + \gamma e^2 V + 2\gamma e V U + 2\gamma e V^2 + 2\gamma U V^2 \\
&\quad + U^2 R + V^2 R + e^2 R + 2eUR + 2eVR + 2UVR) \\
&= E(\gamma^2\beta e^3 V^2 + 2\gamma^2\beta e^2 V^3 - \gamma e^3 R^2 - \beta^2\alpha U^2 V^3 \\
&\quad - 2\beta^2\alpha U^3 V^2 - \beta^2\gamma U^3 V^2 - 2\beta^2\gamma U^2 V^3 + \beta U^3 R^2 \\
&\quad - \alpha^2\beta U^2 e^3 - 2\alpha^2\beta e^2 U^3 - \beta R^2 V^3 + 2\gamma^2\alpha e^3 V^2 \\
&\quad + 2\alpha^2\gamma e^3 U^2 + R^3 U^2 + R^3 V^2 + R^3 e^2 - \alpha e^3 R^2),
\end{aligned}
$$

$$
\begin{aligned}
2E(QY)E(PYW) &= 2E[(-\gamma e+\beta U+R)(U+V+e)]E[(-\beta V+R-\alpha e)(U+V+e)(\alpha U+\gamma V+R)] \\
&= 2E(-\gamma e^2+\beta U^2)E(-\beta\gamma V^3) \\
&= 2\gamma^2\beta E(e^2)E(V^3)-2\beta^2\gamma E(U^2)E(V^3),
\end{aligned}
$$

$$
\begin{aligned}
2E(PY)E(QYW) &= 2E[(-\beta V+R-\alpha e)(U+V+e)]E[(-\gamma e+\beta U+R)(U+V+R)(\alpha U+\gamma V+R)] \\
&= 2E(-\beta V^2-\alpha e^2)E(\alpha\beta U^3) \\
&= -2\alpha\beta E(V^2)E(U^3)-2\alpha^2\beta E(e^2)E(U^3),
\end{aligned}
$$

$$
\begin{aligned}
2E(YW)E(QPY) &= E[(U+V+e)(\alpha U+\gamma V+R)]E[(\gamma e+\beta U+R)(\beta V+R-\alpha e)(U+V+e)] \\
&= 2E(\alpha U^2+\gamma V^2)E(\gamma\alpha e^3) \\
&= 2\gamma\alpha^2E(U^2)E(e^3)+2\gamma^2\alpha E(V^2)E(e^3),
\end{aligned}
$$

$$
\begin{aligned}
E(Y^2)E(QPW) &= E[(U+V+e)^2]E[(\gamma e+\beta U+R)(-\beta V+R-\alpha e)(\alpha U+\gamma V+R)] \\
&= E(U^2+V^2+e^2)E(R^3) \\
&= E(U^2)E(R^3)+E(V^2)E(R^3)+E(e^2)E(R^3),
\end{aligned}
$$

$$
\begin{aligned}
E(QW)E(PY^2) &= E[(-\gamma e+\beta U+R)(\alpha U+\gamma V+R)]E[(-\beta V+R-\alpha e)(U+V+e)^2] \\
&= E(\alpha\beta U^2+R^2)E(-\beta V^3-\alpha e^3) \\
&= -\alpha\beta^2E(U^2)E(V^3)-\alpha^2\beta E(U^2)E(e^3)-\beta E(R^2)E(V^3)-\alpha E(R^2)E(e^3),
\end{aligned}
$$

$$
\begin{aligned}
E(PW)E(QY^2) &= E[(-\beta V+R-\alpha e)(\alpha U+\gamma V+R)]E[(-\gamma e+\beta U+R)(U+V+e)^2] \\
&= E(-\beta\gamma V^2+R^2)E(-\gamma e^3+\beta U^3) \\
&= \beta\gamma^2E(V^2)E(e^3)-\beta^2\gamma E(V^2)E(U^3)-\gamma E(R^2)E(e^3)+\beta E(R^2)E(U^3).
\end{aligned}
$$

**Part 2. Proof of the equivalence between equations (10), (11) and equations (12) and (13)**

Calculating the joint cumulants of the mean zero variables, we have

$$
\begin{aligned}
\kappa^{1,3}_{Y,W} &= E[W^3Y]-3E[WY]E[W^2] \\
\kappa^{3,1}_{Y,W} &= E[WY^3]-3E[WY]E[Y^2] \\
\kappa^{2,2}_{Y,W} &= E[W^2Y^2]-E[W^2]E[Y^2]-2E[WY]E[WY] \\
\kappa^{1,4}_{Y,W} &= E[WY^4]-4E[Y^3]E[WY]-6E[WY^2]E[Y^2] \\
\kappa^{2,3}_{Y,W} &= E[W^3Y^2]-3E[WY^2]E[W^2]-6E[W^2Y]E[WY]-E[W^3]E[Y^2] \\
\kappa^{3,2}_{Y,W} &= E[W^2Y^3]-3E[W^2Y]E[Y^2]-6E[WY^2]E[WY]-E[Y^3]E[W^2]
\end{aligned}
$$

Now we start from equation (12),

$$
\begin{aligned}
0 &= \kappa^{1,3}_{Y,W} - \alpha^2\kappa^{3,1}_{Y,W} - (\gamma+\alpha)(\kappa^{2,2}_{Y,W} - \alpha\kappa^{3,1}_{Y,W}) \\
&= \kappa^{1,3}_{Y,W} - \gamma\left(\kappa^{2,2}_{Y,W} - \alpha\kappa^{3,1}_{Y,W}\right) - \alpha\kappa^{2,2}_{Y,W} \\
&= E[W^3Y] - 3E[WY]E[W^2] \\
&\quad - \gamma(E[W^2Y^2] - E[W^2]E[Y^2] - 2E[WY]E[WY] - \alpha(E[WY^3] - 3E[WY]E[Y^2])) \\
&\quad - \alpha(E[W^2Y^2] - E[W^2]E[Y^2] - 2E[WY]E[WY]),
\end{aligned}
$$

which is equivalent to equation (10). Reorganizing equation (10) we get the moment to construct the GMM estimator:

$$
\begin{aligned}
0 = E[&(W^2 - \gamma WY - \alpha WY + \alpha\gamma Y^2)WY - (W^2 - \gamma WY - \alpha WY + \alpha\gamma Y^2)\mu_{wy} \\
&- (\mu_{wy} - \gamma\mu_{yy})(W(W-\alpha Y)) - (\mu_{ww} - \gamma\mu_{wy})((W-\alpha Y)Y)],
\end{aligned}
$$

with $E[\mu_{ww} - W^2] = 0$, $E[\mu_{yy} - Y^2] = 0$ and $E[\mu_{wy} - WY] = 0$. Similarly, we can establish equation (11) from equation (13). $\square$

# E Data Construction and Variables

In this study, we establish a unique faculty-level data, combining faculty salary records with faculty demographics, educational background, and professional experience obtained through online searching, and publication metrics scraped from Google Scholar. Here, we provide more details on the data construction process and variable definitions.

Administrative salary data for all tenure-track faculty members at these universities were extracted from Georgia's Open Government Data Portal.[23] To link the publicly available faculty salary data with scraped public information on faculty member's educational background, career trajectory, work experience, and publication metrics, we conduct the following procedures.

First, to obtain data on faculty-level wages and separations, we retrieve salaries from 2010 through 2022 from Georgia's Open Government Data Portal (Open Georgia, https://open.ga.gov/). This payroll data set provides information on the annual compensation and the employee's full name, job title, and university of employment. It allows us to track both the salary and the transition history for faculty members working in the USG. We confine the sample to the academic faculty and filter out non-academic employees by imposing restrictions on the title. In other words, only employees whose titles contain "professor" would be included in the sample. Based on the titles in the payroll record, we generate three *Title* dummies to indicate whether faculty are titled "Assistant", "Associate", or "Full" professors.

In addition, to create covariates capturing faculty-specific confounding factors that affect both salaries and faculty separation decisions, we search online for faculty members' department profiles and personal websites using keywords including the faculty member's full name, job title, and affiliation. We scrape information on the faculty member's gender, department of employment (used to infer the field of specialization), educational background, and work history from their online profile and curriculum vitae. Specifically, we observe the gender and department of employment of each faculty member, which helps us to construct the gender and field dummies. We rely on three ways to determine faculty's gender. The primary approach is to use the photos on their department profiles, personal websites, or LinkedIn profiles, etc. We also consult the gendered pronouns used by faculty (e.g., in his/her biography, self-introduction, and research introduction, etc.) as a complementary resource. For example, if a faculty member uses "she/her" in her biography to refer to herself, then we assign "female" to that faculty member. Occasionally, neither the photo nor the self-use gendered pronouns are available. In this case we turn to the gendered pronouns used by a third-party. For instance, we assign gender based on the gendered pronouns used by students to refer to the faculty member in reviews on *RateMyProfessors.com* (https://www.ratemyprofessors.com) or the gendered pronouns for the faculty member in news on the institutional websites.[24] Based on the assigned gender, we then generate a dummy variable *Female* that equals one if the faculty member is recognized as female and zero if the faculty member is male. We infer and assign the field to faculty based on the name of department of employment. We generate a set of dummy variables indicating the field to which the faculty belongs based on the Major Field Categories classified by the National Survey of Student Engagement (NSSE).

For the educational background, we collect information on the faculty's degree-granting institutions, including doctorate, masters, and bachelors degrees, along with the year of graduation

[23]Data source: Open Georgia, https://open.ga.gov/.

[24]In some rare cases that a faculty member use gender-neutral pronouns such as "they," we rely on the third-party-used gendered pronouns to assign gender.

from each institution. For the work history, we collect information on faculty members' post-doctoral and work experience, including the name of previous employer(s) and the work duration with each employer. Later in this Appendix, we will discuss in more detail about the construction of covariates according to the information on educational background and work history.

Moreover, leveraging the advantage that research productivity is arguably a good proxy of faculty's research ability and can be quantitatively measured by publication statistics, we include controls for research productivity to reduce omitted variable bias. To do this, we collect data on research productivity by scraping publication metrics of each faculty member from Google Scholar.[25] We create two variables: *lnHindex* and *lnCitation*, as measures of faculty's observed research productivity. They are defined as the logarithm of the H-index and total number of citations, respectively.

Our salary measure is based on the gross pay. Because the payroll data are measured according to the calendar year while the compensation and recruitment in the USG are based on the academic or fiscal year, the payroll record in the year when the job starts or terminates contains only a share of the annual compensation.

For example, faculty members who left their campus of employment in Fall 2016 would still see their compensation for Spring 2016 appear in their 2016 payroll record. Therefore, for faculty members who left their original university of employment and moved to a new university, their compensation usually dropped significantly in the year when the separation occurred (i.e., the termination year), or put differently, in their last compensation record. A similar pattern applies to faculty members who joined the university in the sample during 2010-2022. That is, there would be a jump in salaries in the year after the starting year. To precisely measure transitioning faculty members' compensation, we constructed a mean salary variable, *MeanSalary*, by taking the average of gross pay excluding the first and/or the last salary records.[26] Formally, for a transitioning faculty member $i$ who worked in campus $s$ during time period $t, t+1, ..., T$, the mean salary $MeanSalary_i$ is calculated according to the following formula:

$$MeanSalary_i = \begin{cases} \frac{1}{T-t-1}\sum_{j=t+1}^{T-1} GrossPay_{ij} & \text{if } T-t-1 > 3 \\ \frac{1}{T-t}\sum_{j=t+1}^{T} GrossPay_{ij} & \text{if } T-t-1 \leq 3 \text{ and } T == 2018 \\ \frac{1}{T-t}\sum_{j=t}^{T-1} GrossPay_{ij} & \text{if } T-t-1 \leq 3 \text{ and } T < 2018 \end{cases}$$

where $GrossPay_{ij}$ denotes the gross pay for faculty member $i$ in calendar year $j$. The mean salary variable for non-transitioning faculty members corresponds to the average gross pay from 2010 to 2022. Using the mean salary variable, we define the *lnSalary* variable as the logarithm of the mean salary, i.e. $lnSalary_i = \log(MeanSalary_i)$.

As noted before, we create a set of control variables based on faculty members' educational background and work history. *GUndergrad* and *GPhD* are variables indicating whether faculty received bachelor's or post-graduate degrees from institutions in the USG, respectively. *ForeignUndergrad* and *ForeignPhD* are dummy variables indicating whether the degree-granting institutions are foreign universities. *YrsSinceGrad* is a discrete variable measuring the number of years since

[25] Google Scholar (GS), which has been argued to have the best coverage of conferences and most journals (Meho and Yang 2007).

[26] If the transitioning faculty member has more than three payroll records, the mean salary is calculated by excluding both the first and the last records. If the faculty only has two or three payroll records, the construction of the mean salary depends on whether s/he left the campus of employment: if the faculty left, then we exclude the last record; if not, then we drop the first record. Faculty that only have a single payroll record are excluded from the sample.

graduation. It is constructed by calculating the number of years between 2022 and the year when the faculty member obtained his/her highest degree. *AnyPostdoc* is a discrete variable that measures the number of postdoctoral spells.[27] *YrsPostdoc* is a discrete variable that measures the total years of postdoctoral experience. Lastly, to distinguish faculty who ever took an administrative job, we use a dummy variable *EverAdmin* as an indicator for taking administrative positions such as dean, provost, director, or chair of a department.

Our sample consists of 4289 tenure-track faculty affiliated with the aforementioned three USG institutions from 2010 to 2022. We exclude faculty who passed away, retired, or were fired during the sample period, as they are regarded as "natural death" and "involuntarily" separations. Since faculty layoffs are usually a result of violations of law or university policy, such as involvement in a sexual harassment lawsuit, we identify them by checking university and local news. Retirements are confirmed by checking the department's website, such as looking for the "Emeritus" status. Deaths are verified by checking memorials, university news, and other online sources. We further exclude observations with missing values on graduation year, length of postdoctoral experience, and publication statistics, which results in a final sample containing 3,002 tenure-track faculty members.[28]

[27]Any research position post-graduation in any research institution such as universities, research centers, and laboratories is coded as a postdoctoral spell. Different positions in the same institution are combined to one spell. Positions in two different institutions are coded as two spells.

[28]Among these 4289 faculty members, 1247 do not have Google Scholar accounts and hence miss publication statistics, 10 lack information about the length of postdoctoral experience, and 127 lack the graduation year of their highest degree.

# F Heterogeneity of Monopsony Power

Here, we examine whether faculty members with different observed attributes experience different levels of monopsony power by estimating labor supply elasticities and exploitation rates across subgroups. We adopt the preferred model in the main analysis and estimate the exploitation rate separately for each subgroup by field (with more outside options v.s. fewer options), citizenship (U.S. Born v.s. Non-U.S. Born), gender (Male v.s. Female), and tenure status (Non-tenured v.s. Tenured), using LSZ and the proposed methods. Results are summarized in the Appendix Figure A.1. Because dividing the sample by subgroup further reduces the sample size, some of the estimates lack precision for both the LSZ and the proposed methods. Given this, Figure A.1 suggests that the observed monopsony power is primarily driven by faculty members who are foreign-born, tenured, male, and work in fields with limited outside opportunities beyond academia.[29] These findings align with previous studies (e.g., Goolsbee and Syverson 2023; Yu and Flores-Lagunes 2024) that found monopsony power to be more pronounced among these groups. Furthermore, for subgroups in which we obtain a statistically significant gamma, we observe a consistent pattern: the estimated exploitation rates by LSZ moments (shown in the blue box) are generally smaller than those estimated by our approach (shown in the red box), which accounts for measurement error. This once again highlights the need to address measurement error in estimation to alleviate bias.

[29] Fields with fewer out-of-academia options consist of: ARTS, HUMANITIES & MEDIA, SOCIAL SCIENCE & EDUCATION, SOCIAL SERVICE PROFESSIONS, PHYSICAL SCIENCES, MATH, and OTHERS. Fields with more out-of-academia options includes: BIOLOGICAL SCIENCES, CS, BUSINESS, ENGINEERING, and HEALTH PROFESSIONS.