Identifying Models With Mismeasured Endogenous Regressors Without Instruments: an Application to Monopsony in Academic Labor Markets

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January, 2025

Abstract

We extend the linear triangular structural model of Lewbel, Schennach, and Zhang (2024) to account for measurement errors in the endogenous regressor. Using higher-order moments, we identify the causal effect and distributions of unobservables without relying on instrumental variables or repeated measurements. We apply this approach to study monopsony power in the labor market for university professors at public research universities within the University System of Georgia, addressing endogeneity and measurement error concerns related to faculty salaries in the absence of suitable instruments. Our findings reveal significant monopsony power, with a robust exploitation rate of 36%, and demonstrate that neglecting measurement error would lead to substantial underestimation.

Keywords: Triangular System, Endogeneity, Measurement Error, Identification, Monopsony, Labor Market
JEL Classification: C3, C13, J42

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1 Introduction

Linear regression models with endogenous regressors are typically identified using exclusion restrictions, requiring instrumental variables that correlate with the endogenous regressor but not with the errors in the outcome equation. However, valid instruments are sometimes unavailable in empirical settings, leading to the development of methods that address endogeneity without relying on exclusion restrictions (e.g., Rigobon 2003; Klein and Vella 2010; Lewbel 2012). A recent contribution is Lewbel, Schennach, and Zhang (2024), which studies a triangular two-equation system where endogeneity arises from a common unobserved factor and achieves identification using higher moment restrictions rather than instruments.

A key assumption in Lewbel, Schennach, and Zhang (2024) (hereafter LSZ) is that the common unobservable is a scalar. This is not an innocuous restriction.[1] For example, in returns-to-schooling models, unobserved ability is often thought to simultaneously influence both educational attainment and future earnings. Assuming a scalar common latent variable implies that unobserved ability alone drives error correlations, excluding the possibility of measurement error in the endogenous regressor. However, empirical research often involves noisy or contaminated measures of the true variable. As Card (2001) points out, OLS estimates in returns-to-schooling models frequently exhibit downward bias, likely driven by an attenuation bias from measurement error in addition to the upward bias from the unobserved ability. Indeed, measurement error in self-reported educational attainment has been well-documented (see Black, Sanders, and Taylor 2003).

This paper shows that the coefficient of a mismeasured endogenous regressor can still be identified without using instruments, under the assumption that the measurement error is independent of other latent variables with unknown distributions. As in LSZ, we assume mutual independence among all error components in the triangular structural model and use the resulting moment constraints. Relaxing the single common factor assumption

[1]As LSZ notes in Supplement D for additional results of their application, discrepancies between their proposed moment estimates and those from valid IV moments are likely due to violating this assumption.

introduces challenges because, unlike LSZ, an additional unobservable appears in both equations of the triangular system. Addressing this requires a different set of covariance information and higher-order joint characteristic functions. The identification results in this paper are most useful when the primary interest lies in estimating the causal effect (the slope coefficient). For cases where the unknown distributions of latent variables are of interest, we show that they can be point-identified under extra assumptions about the distribution of the measurement error.

We extend the identification results to a more general model with a vector of common unobservables, with measurement error as a special case. This generalization is particularly relevant in empirical contexts where multiple unobserved factors exist, each contributing differently to error correlations. Despite the added complexity, estimation remains straightforward, as easy-to-implement GMM estimators can be constructed using low-order moments. Furthermore, we provide overidentifying moments, enabling more precise estimates than those obtained with exact-identifying moments alone.

Our identification approach is most well-suited for settings where the structural model motivated by economic theory suggests multiple sources of endogeneity, and traditional instruments are weak or not available. Even when the common unobserved component is a scalar, our moments remain applicable. Moreover, when ordinary instruments are available, higher-order moments can be used alongside instruments to enhance efficiency or test overidentifying restrictions.

We apply our identification results to study monopsony power in the labor market. Evaluating monopsony power typically requires estimating the wage elasticity of labor supply through a model that relates separation or recruitment to salaries. It's widely acknowledged in the literature that salary is endogenous, with unobserved factors, such as ability, affecting both wages and the separation or recruitment probability. In addition, salaries often contain measurement errors due to factors such as unreported compensation (e.g., research grants), unaccounted benefits, stipends, overtime pay, and timing mismatches for new hires. The separation or recruitment model is traditionally identified using instruments, exploiting exogenous changes in policies (e.g., Naidu, Nyarko, and Wang 2016; Bassier, Dube, and Naidu 2021; Staiger, Spetz, and Phibbs 2010) or salary scales (e.g., Ransom and Sims 2010; Yu and Flores-Lagunes 2024). However, exogenous policy changes are rare, and salary scales are not always accessible, especially in empirical settings with limited transparency in pay determination.

This section continues by offering examples of applications where endogeneity and measurement errors present simultaneously, a review of the literature, and the contribution of our empirical application.

1.1 Examples of Mismeasured Endogenous Regressor. Beyond the aforementioned applications, a mismeasured endogenous regressor arises in many other empirical contexts. For example, Dahl and Lochner (2012) study the effect of family income on child achievement and point out the potential for mismeasurement in income data. Kaestner, Joyce, and Wehbeh (1996) estimate a model relating maternal drug use to birth weight, where drug usage is both endogenous and often mis-reported. Similar to our empirical application, Hu, Shiu, and Woutersen (2015) explore a model linking the number of hours worked to wages, and concern errors in the measured wage rate. In all these studies, the model suffers from both endogeneity due to a common unobserved factor and measurement error in the regressor. Applying LSZ's method in such settings contradicts its modeling assumptions and is therefore problematic.

More generally, in many cases, the unobservables consist of multiple latent variables. For instance, 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, and more.

1.2 Literature The identification of a linear triangular structural model without exclusion restrictions has been previously studied by Rigobon (2003), Klein and Vella (2010), and Lewbel (2012). All these studies use heteroskedasticity as a source of identification, imposing restrictions on how the variance, covariance, or higher moments of errors depend on the regressors. In contrast, our approach allows for either heteroskedasticity or homoskedasticity.

This paper is also related to the literature on using higher moments to identify error-in-variable models (Cragg 1997; Dagenais and Dagenais 1997). These models 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 substantial 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. By contrast, we focus on empirical settings where such auxiliary information is unavailable, so their methodologies do not apply.

1.3 Monopsony Power in University System of Georgia (USG). There has been burgeoning interest about the monopsony power since 2010.[2] Monopsony is naturally linked to "thin" labor markets where the opportunities to change jobs are hard to find, giving employers power to set the wage (Manning 2003b). A typical example of occupations that face a "thin" labor market is university professors, who work in jobs requiring specialized knowledge and are likely to have fewer outside job options. More studies are beginning to examine monopsony power in the university faculty labor market. For example, Goolsbee and Syverson (2023) and Yu and Flores-Lagunes (2024) studied monopsony in U.S. academia. Both studies adopt an instrumental variable (IV) strategy. The former draws on university-level salary data from IPEDS, while the latter uses faculty-level salary data from the University of California system.

The growing blue-red state divide has shaped significant differences in higher education policies across the United States. Republican-led, or "red" states, have implemented reforms that alter traditional faculty protections, such as tenure, sparking debates on academic freedom and job security. Georgia, among the red states, serves as a prominent

[2]See Ashenfelter et al. (2022), Manning (2021), and Card (2022) for reviews.

example of this trend. 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).[3] 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 in USG, influence labor supply, and increase job turnover—all of which could in turn affect universities' ability to set salaries.

Debates on the Georgia system abound, yet little analysis has been conducted on this. Our application fills this gap, examining the monopsony power in USG using the developed new method. We start by setting up an economic model motivating the linear structural model. The model is then estimated using a novel and comprehensive faculty-level dataset on three research R1 universities within the University System of Georgia. The data combines administrative salary records with faculty characteristics we scraped online, spanning from 2010 to 2022. This dataset is unique and has not been used in other studies. The newly acquired faculty-level data allow us to estimate university-level monopsony power for the USG. Moreover, the identification strategy eliminates questions concerning the validity of instruments, and yields consistent estimates even when salary is both endogenous and mismeasured.

We find evidence of monopsony, with the exploitation rate—a common measure of monopsony power—robustly estimated at 36%. By comparing our results with those from standard methods, we highlight the importance of addressing measurement error when evaluating monopsony power, as ignoring the potentially mismeasured salaries would lead to an underestimation of monopsony power. Our empirical analyses complement prior work by providing novel evidence that monopsony power exists in a public university system in a red state. Moreover, we demonstrate that its intensity varies over time,

[3]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*".

corresponding with different phases of faculty governance reforms.

The rest of the paper proceeds as follows. Section 2 provides the setup and identification results, and their applicability in practice. Section 3 presents the evaluation of monopsony power in the labor market using our proposed method. Section 4 concludes.

2 Model Identification and Estimation

2.1 Identification

Consider the model

$$Y^* = U + V \tag{1}$$

$$W = \gamma Y^* + \beta U + R, \tag{2}$$

where U, V, R are unobserved errors with unknown distributions. However, the endogenous variable Y^* is unobserved, and instead, we observe Y, where $Y = Y^* + e$. We assume that e is a classical measurement error and maintain the other assumptions in LSZ, such that U, V, R and e are mutually independent and mean zero.

For example, in returns-to-schooling models, W represents wages, Y is schooling, U captures an individual's unobserved ability, and e is the measurement error in educational attainment.

Substituting out the unobserved Y^* in equations (1) and (2) yields

$$Y = U + V + e \tag{3}$$

$$W = \gamma Y + \beta U - \gamma e + R. \tag{4}$$

Now we have two common unobserved errors in both equations. Note that the moment constraint (7) in Lemma 1 of LSZ does not hold without additional assumptions. Even if U, V, R and e are assumed to be mutually independent, observe that $E[(W - \gamma Y)(W - \gamma Y - \beta Y)Y] = E(\alpha \gamma e^3)$, which is nonzero unless the distribution of e is symmetric, i.e., $E(e^3) = 0$.

Similarly, 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. 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), and Dong, Otsu, and Taylor (2022).

Instead, we show that a different set of moment restrictions hold without imposing assumptions on the distribution of the measurement error. Substituting (3) into equation (4) gives:

$$W = \gamma V + \alpha U + R, \quad \text{with} \quad \alpha = \gamma + \beta. \tag{5}$$

We establish the identification of γ and α 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.*

Proving identification of γ and α makes use of the characteristic function representation of random variables. Below, we formally define the notation used in the main theorem.

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 (3) and (5) hold. Define the moment*

$$g_p(\alpha,\gamma) \equiv \kappa_{Y,W}^{1+p,3} - (\gamma+\alpha)\kappa_{Y,W}^{2+p,2} + \alpha\gamma\kappa_{Y,W}^{3+p,1}.$$

The moment satisfies the constraint

$$g_p(\alpha,\gamma) = 0 \tag{6}$$

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

$$g_q(\alpha,\gamma) = 0, \quad \text{and} \quad g_{\tilde{q}}(\alpha,\gamma) = 0$$

point identify the parameters α and γ, with α being equal to the larger root.

The proof is in Appendix A. 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.

Next, we use the relationships between cumulants and moments[4] to derive low-order moments for constructing GMM estimators.

Lemma 1. *Let Assumption 1, equations (3) and (5) hold, then the following two moment constraints hold:*

$$\begin{aligned} &cov[(W-\gamma Y)(W-\alpha Y), YW] = \\ &\quad E\left(WY-\gamma Y^2\right)E\left(W^2-\alpha YW\right) + E\left(W^2-\gamma YW\right)E\left(WY-\alpha Y^2\right) \end{aligned} \tag{7}$$

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

$$
\begin{aligned}
&cov[(W-\gamma Y)(W-\alpha Y), Y^2 W] = \\
&\quad 2E[(W-\gamma Y)Y]E[(W-\alpha Y)YW] + 2E[(W-\alpha Y)Y]E[(W-\gamma Y)YW] \\
&\quad + E(Y^2)E[(W-\gamma Y)(W-\alpha Y)W] + E(YW)E[(W-\gamma Y)(W-\alpha Y)Y] \\
&\quad + E[(W-\gamma Y)W]E[(W-\alpha Y)Y^2] + E[(W-\alpha Y)W]E[(W-\gamma Y)Y^2]. \qquad (8)
\end{aligned}
$$

In particular, we can show that Equations (7) and (8) are equivalent to the moment constraints

$$g_0(\alpha, \gamma) = 0, \qquad (9)$$

$$g_1(\alpha, \gamma) = 0. \qquad (10)$$

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

Based on equation (6), 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 B.

Note that Theorem 1 and Lemma 1 hold without requiring the distributions of U, V, R and e to be known. Next, 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 (3) and (5) 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 α and γ are point identified, then the distributions of U, V and R are point identified.*

The proof is provided in Appendix A. 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. 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 (7) and (8) 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 α and γ, can be estimated.

2.2 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 $\{U_1 \ldots U_K\}$ denote a set of unobservables indexed by k. Consider the model

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

which can be rewritten as

$$Y = \sum_{k=1}^{K} U_k + V, \quad W = \sum_{k=1}^{K} \alpha_k U_k + \gamma V + R. \tag{11}$$

The model of mismeasured endogenous variable in section 2.1 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.

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 $U_1, \dots, U_K$, V, and R are mean zero and mutually independent.*

Theorem 2. *Let Assumption 2 and model (11) hold. Let*

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

For any $p \in \{0, 1, \dots\}$,

$$g_p(\alpha_1, \dots, \alpha_K, \gamma) = 0. \tag{12}$$

Let Θ be a bounded set and $\theta \equiv (\alpha_1, \dots, \alpha_K, \gamma) \in \Theta$. Define a mapping $F(\theta) : \Theta \to F(\Theta)$ such that $F(\theta) \equiv [(g_0(\theta), \dots, g_K(\theta))']$. 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 $\theta = (\alpha_1, \dots, \alpha_K, \gamma)$ is globally identified over Θ.

The proof is provided in Appendix A. Higher-order relations between cumulants of observed and unobserved variables are used to establish equation (12). 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 $\kappa^{3,1}_{Y,W}\kappa^{3,2}_{Y,W} - \kappa^{4,1}_{Y,W}\kappa^{2,2}_{Y,W} \neq 0$ 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 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.[5] 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 (11) 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* ϕ_{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* ξ *of degree* $\leq K$*. Similarly, let* ϕ_V, f_V *and* ϕ_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* $\phi_R(\xi) = f_R(\xi)\exp(P_K(\xi))$*.*

[5] As shown in Rao (1971), under the framework of model (11) 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.

2.3 Moments with Covariates

Here we derive the moments required for identification of the model in section 2.1 with covariates. Assume X is a K vector of covariates. The model with covariates is

$$Y = \delta' X + U + V + e \tag{13}$$

$$W = \gamma Y + \tau' X + \beta U - \gamma e + R \tag{14}$$

where δ and τ are vectors of coefficients, which include constant terms.

Define $\tilde{Y}$, $\tilde{W}$, Q, and P by

$$\tilde{Y} = Y - \delta' X, \quad \tilde{W} = W - (\gamma\delta + \tau)' X,$$
$$Q = W - \gamma Y - \tau' X, \quad P = W - (\gamma + \beta) Y + (\beta\delta - \tau)' X.$$

We can extend moment conditions in Lemma 1 to incorporate covariates and construct the following moments for GMM estimation:

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

along with

$$E[\tilde{Y}\tilde{W} - \mu_{\tilde{y}\tilde{w}}] = 0, \quad E[\tilde{Y}^2\tilde{W} - \mu_{\tilde{y}\tilde{y}\tilde{w}}] = 0, \quad E[QX] = 0, \text{ and } E[\tilde{Y}X] = 0,$$

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.

3 Application: Monopsony in Academia

In this section, 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 begin with a brief introduction to monopsony theory and outline the ’separation-based’ approach used to estimate the wage elasticity of separations, labor supply elasticity, and the exploitation rate—a common measure of monopsony power. We followed by discussing challenges in the empirical analysis, including the endogenous and mismeasured salary variable and the absence of commonly used salary scale instruments (IVs) for the endogenous regressor, making this a well-suited example to illustrate the application of our method. Next, we describe the data and present the estimation results, comparing them to those obtained using standard methods.

3.1 Conceptual and Empirical Model

The idea of firms’ 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. This idea has been further developed by Manning (2003a), who demonstrated that firms can be monopsonists despite the existence of many competitors in a frictional labor market. Manning’s framework has been employed in the analysis of monopsony power for several labor markets (Matsudaira 2014; Ransom and Sims 2010, among others), including the labor market of university professors (Yu and Flores-Lagunes 2024). In such framework, the extent of the monopsony power depends on the wage elasticity of labor supply faced by the employer. To see this, consider that the university 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:

$$\min_{N} w(N)N,\ s.t.\ Y(N) = \bar{Y} \tag{15}$$

where $w(N)$ denotes the wage level and $Y(N)$ represents the production function.[6] Solving Equation (15), we obtain the following key relationship,

$$E = \frac{\text{MRP} - w}{w} = \frac{1}{\varepsilon} \tag{16}$$

Equation (16) links the rate of exploitation (E), a common index for measuring the extent of monopsony power, which is defined as $(MRP - w)/w$, to 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 ($\varepsilon = \infty$), the university possesses no monopsony power and pays faculty members the equivalent of their marginal revenue product (MRP), i.e., $w = \text{MRP}$. Alternatively, if $\varepsilon = 5$, the rate of exploitation rate is 20% and the university pays faculty members 80% of their MRP.

Credibly estimating ε becomes the pillar of empirical analyses on the monopsony power. Researchers has proposed several estimation strategies to quantify ε in various empirical settings (see Sokolova and Sorensen 2021, for a review). A canonical model, proposed by Manning (2003a), leverages the linear relationship between ε and the wage elasticity of recruits (ε_r) and the wage elasticity of separations (ε_s) in the steady state, i.e., $\varepsilon = \varepsilon_r - \varepsilon_s$. Under the assumption that in the steady state, one university's recruits by offering higher wages should be another university's quits (i.e., $\varepsilon_r = -\varepsilon_s$), one can show that $\varepsilon = -2\varepsilon_s$. Therefore, ε can be obtained by estimating ε_s.

To estimate the wage elasticity of separations to the university (ε_s), we consider the following model:

$$Separation_i = \gamma \ln Salary_i^* + \tau' X_i + \epsilon_i \tag{17}$$

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, measured by the average annual salary of faculty member i during his/her employment period at the university from 2010 to 2022. ϵ_i denotes the error term in the separation equation. We include a rich set of covariates (X_i) to control for faculty

[6]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.

attributes, work experience, educational background, and research ability. These variables are defined and discussed in detail in the Data section (see Section 3.2). The wage elasticity of separation ε_s is then estimated by γ divided by the sample mean separation rate $\bar{s}$.

Salaries are widely acknowledged as endogenous in the separation equation. Despite extensive controls for observables, omitted variables may still be a concern. For instance, while the model controls for research ability via publication metrics, it does not account for other productivity aspects, such as teaching and service, which likely correlate with separation probability. The salary variable is also subject to measurement error (denoted as e_i). 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, 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.

Given the endogenous and mismeasured salary variable, the observed salaries (denoted as $\ln Salary_i$, measured in logarithm) can be written as:

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

and the separation equation is given by:

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

where U_i captures the common factor that simultaneously determines salaries and separations. V_i represents the unobservables that are specific to salaries, and R_i denotes the error term that only enters the separation equation, i.e., the unobservables specific to the separation variable.[7] Plugging the observed salary function back into the separation

[7]Therefore, the error term ϵ_i in Equation (17) equals $\beta U_i + R_i$.

equation, the model becomes:

$$Separation_i = \gamma \ln Salary_i + \tau' X_i + \beta U_i + R_i - \gamma e_i \tag{18}$$

This "separation-based" approach, along with other strategies, typically involves instrumental variables to address the endogeneity of wages. However, valid instruments for wages in academia are 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). However, such an 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 University System of Georgia. The endogenous salary variable, the lack of ideal IVs, and the measurement error in the salary variable make this a well-suited application for the technique developed in this paper.

3.2 Data

This empirical application leverages a unique and comprehensive faculty-level dataset on the public university system of Georgia, focusing on three primary research universities in the University System of Georgia: 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. Administrative salary data for all tenure-track faculty members at these universities were extracted from Georgia's Open Government Data Portal.[8] Utilizing each faculty member's full name, title, and department and university of employment, we conducted online searches to gather information on gender, educational history, and work experience from faculty websites, CVs, and LinkedIn profiles. We further retrieved data on research productivity by searching each faculty member's Google Scholar

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

page and extracting their publication metrics, including the total number of citations and H-index.

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.[9]

We control for faculty attributes including job title ($Title$), field of specialization ($Field$), gender ($Female$), and citizenship ($ForeignBorn$).[10] Four variables are created to control for confounding factors related to faculty's experience. $YrsSinceGrad$ 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, and $EverAdmin$ denotes a binary indicator that equals one if the faculty member ever served as dean, provost, director, or chair of a department. For educational background, we construct four binary indicators: $GPhD$ and $GUndergrad$ flag whether the faculty member is an undergraduate or graduate alumni of the three Georgia universities, while $ForeignPhD$ and $ForeignUndergrad$ signify whether the faculty member obtained Ph.D. or Bachelor's from foreign institutions. Lastly, we use the logarithm of H-index ($lnHindex$) and the logarithm of the total number of citations ($lnCitation$) as two measures of research productivity.[11]

Table 1 summarizes descriptive statistics of the outcome variable $Separation$, the

[9]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.

[10]We infer faculty members' field of specialization by their working department or school. We classified the field into 9 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, we do not directly observe faculty's nationality from our data. Alternatively, we use the country where faculty members received their undergraduate degree as a proxy.

[11]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.

salary variable $\ln Salary$, 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. We further exclude observations with missing values on graduation year, length of postdoctoral experience, and publication statistics. The final dataset used contains 3,002 tenure-track faculty members.[12]

3.3 Results

We start by estimating Equation (18) using the method of Lewbel, Schennach, and Zhang (2024) (henceforth LSZ estimator) and the method developed in this paper (henceforth LSZ-error estimator), comparing with estimates using the simple OLS. We present in Table 2 the results of γ, β, and the estimated labor supply elasticity ε, along with the corresponding rate of exploitation (E) for OLS (in Panel A), LSZ estimator (in Panel B), and LSZ-error estimator (in Panel C). Columns (1), (4), and (8) show the results from the baseline model. It controls for gender, research ability, and years since graduation variables. We subsequently include additional controls for field, title, university, and citizenship indicators in Columns (2), (5), and (8), and educational and experience controls in Columns (3), (6), and (9). Failing to address the endogeneity and measurement error concerns, the OLS estimates of γ 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 endogenous salaries, the LSZ estimator suggests a significantly higher labor supply elasticity, with the estimated γ increasing from -0.08 to -0.8. The labor supply elasticity is estimated at approximately 6.5 in the preferred model, which is about ten times

[12] 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.

larger than that obtained from the simple OLS model. This implies an exploitation rate of about 15%, suggesting that faculty members are paid approximately 15% less than their marginal revenue product. Panel C suggests that the estimated labor supply elasticities in Panel B are likely overstated, which consequently leads to an underestimated exploitation rate.[13] Taking into consideration both endogeneity and measurement error, Column (9) reports the estimated γ at -0.34, with the corresponding labor supply elasticity estimated at around 3 and the exploitation rate at 36%.

Table 2 provides robust evidence of monopsony power within the University System of Georgia. It's 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 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.[14][15]

[13]In other words, the LSZ estimate may be more biased relative to the true exploitation rate than the LSZ-error estimate.

[14]To gauge the extent to which this difference is related to the methodological differences, we conduct a supplementary analysis comparing 2SLS, LSZ, and LSZ-error estimates using the University of California data from Yu and Flores-Lagunes (2024). The results are summarized in Appendix Table D.1. As previously discussed, based on the 2SLS estimation, monopsony power is estimated at 7%. Without IVs, the LSZ estimate implies an exploitation rate of 15%, while, further accounting for measurement error, the LSZ-error estimate yields a rate of 13%. Overall, the LSZ-error estimate is closer to the 2SLS estimate compared to the LSZ estimate, highlighting the necessity of accounting for measurement error. Moreover, given the same method, the estimated monopsony power is substantially greater for the USG than for the University of California System. In other words, the methodological differences may not be the primary factors contributing to the differential monopsony power across institutions.

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

Changes in Monopsony Power Over Time

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 the LSZ-error estimates of γ 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.[16] The significant changes in monopsony power observed from 2014 to 2019 align with a period of significant policy changes, during which the USG enacted a series of policy revisions in 2013, 2014, 2016, 2017, and 2018, tightening tenure requirements and strengthening post-tenure review.[17] While these revisions aimed to increase faculty accountability, they also raised concerns about academic freedom and tenure security, likely contributing to higher faculty separations.[18] 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 labor market uncertainty, reduced outside options, and helped universities regain monopsony power under tenure policies that were less favorable to faculty members.

[16]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 separations among different faculty groups in response to policy changes during this period. However, due to the small sample size of the subgroups, it is infeasible to fully explore this hypothesis.

[17]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.

[18]One way to understand the decline in universities' monopsony power during this period is to consider it through the lens of bargaining power. Tenure security is an important amenity associated with the faculty occupation, and the previously discussed adverse changes in tenure policy tend to significantly reduce universities' wage-setting power. These changes are likely reflected in the estimated exploitation rate.

Heterogeneity of Monopsony Power

Following previous studies, 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 LSZ-error methods. Results are summarized in the Appendix Figure C.1. Because dividing the sample by subgroup further reduces the sample size, some of the estimates lack precision for both the LSZ and LSZ-error methods. Given this, Figure B.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.[19] These findings align with previous studies (e.g., Goolsbee and Syverson 2023) 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 LSZ-error (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.

4 Conclusion

A mismeasured endogenous regressor is seen in many empirical works. This paper extends LSZ's method for identifying linear triangular models by simultaneously accounting for endogeneity and measurement errors. Identification is achieved through higher moments under the assumption that unobserved factors are mutually independent. Low-

[19]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.

order moments are provided for GMM estimation. Unlike LSZ, this paper relies on a different set of covariance information, so their results do not encompass ours.

Additional moments can be constructed from moment constraints in Theorem 1 and Theorem 2, resulting in an overidentified model where tests of overidentifying restrictions are applicable. While higher order moments tend to generate noisier results, they are useful when instruments and repeated measurements are not available. Conversely, when standard instruments are available, our proposed moments can be combined with the exclusion restriction to increase efficiency. Furthermore, we show that once the parameters of interest are identified, the distributions of unobservables can be obtained under normalizations.

Lastly, we illustrate that the proposed method is practically applicable by applying it to assess universities' power in setting salaries in the faculty labor market, where faculty salaries are endogenous, likely mismeasured, and appropriate instrumental variables are not available for standard IV estimators. Our approach yields robust estimates based on a data sample of typical size and is easy to implement using standard programming software, such as Stata. Our analysis shows that ignoring measurement error would significantly underestimate monopsony power in the sampled Georgia public universities.

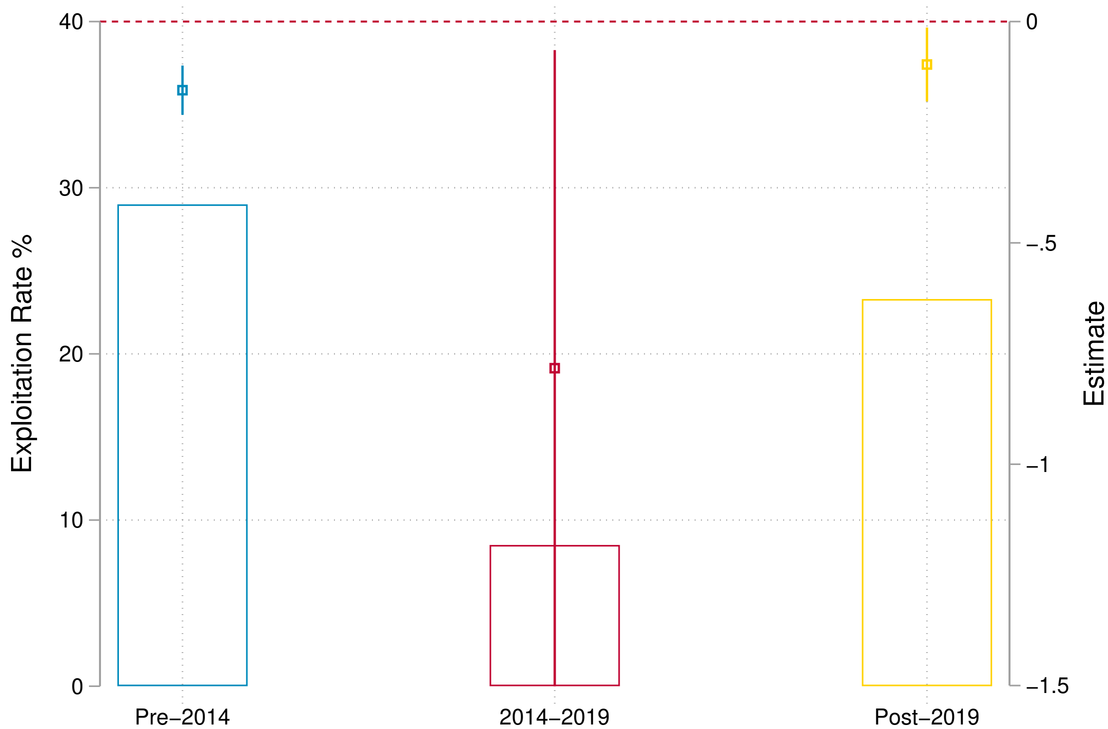

Figure 1: Trends in Monopsony Power

Notes: This figure plots the estimates of γ and their 95% confidence intervals, based on robust standard errors, using the LSZ error 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: 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.

Table 2: Main Results

	Panel A. OLS			Panel B. LSZ			Panel C. LSZ-error		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
γ	-0.083***	-0.078***	-0.084***	-0.780***	-0.744**	-0.804**	-0.347***	-0.321**	-0.338**
	(0.0089)	(0.0089)	(0.0090)	(0.1780)	(0.3390)	(0.3979)	(0.1220)	(0.1318)	(0.1342)
$\log(\beta)$				-0.234	-0.303	-0.236	0.909*	0.971*	1.078*
				(0.2557)	(0.5336)	(0.5907)	(0.5112)	(0.5393)	(0.5940)
Labor Supply Elasticity	0.671	0.635	0.687	6.320	6.042	6.538	2.810	2.602	2.753
Exploitation Rate	1.491	1.574	1.455	0.158	0.166	0.153	0.356	0.384	0.363
N	3002	3002	3002	3002	3002	3002	3002	3002	3002
Baseline	✓	✓	✓	✓	✓	✓	✓	✓	✓
Field + Title + Univ. + Foreign		✓	✓		✓	✓		✓	✓
Education + Experience			✓			✓			✓

Notes: Robust standard errors in parentheses. * p < 0.10, **p < 0.05, *** p < 0.01. This table summarizes the results of γ, β, and the estimated labor supply elasticity ε, along with the corresponding rate of exploitation (E) for OLS (Columns 1-3), LSZ estimator (Columns 4-6), and LSZ-error estimator (Columns 7-9), respectively. Columns (1), (4), and (8) show the results from the baseline model. It controls for gender, research ability, and years since graduation variables. We subsequently include additional controls for field, title, university, and citizenship indicators in Columns (2), (5), and (8), and educational and experience controls in Columns (3), (6), and (9).

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Online Appendix

A Proof

Proof of Theorem 1. **Proof of equation (6) and point identification** 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 $0 \le l < 3+p$, we have the following relationship

$$\begin{aligned}\kappa_{Y,W}^{3+p-l,l+1} &= \left[\frac{\partial^{3+p+1}\Phi_{Y,W}(\zeta,\xi)}{i^{3+p+1}\partial\zeta^{3+p-l}\partial\xi^{l+1}}\right]_{\zeta=0,\xi=0}\\ &= \alpha^{l+1}\kappa_U^{4+p}+\gamma^{l+1}\kappa_V^{4+p}.\end{aligned} \tag{19}$$

Equation (19) 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 κ_U^{4+p} and κ_V^{4+p}, and combine the above three equations into a single equation, which is equation (6). Now verifying equation (6), 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

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

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

Multiplying (20) by $(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1})$ yields

$$
\left(\kappa_{Y,W}^{1+q,3} - \alpha^2\kappa_{Y,W}^{3+q,1}\right)\left(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1}\right) - (\gamma+\alpha)\left(\kappa_{Y,W}^{2+q,2} - \alpha\kappa_{Y,W}^{3+q,1}\right)\left(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1}\right) = 0. \tag{22}
$$

Replacing $(\gamma+\alpha)(\kappa_{Y,W}^{2+\tilde{q},2} - \alpha\kappa_{Y,W}^{3+\tilde{q},1})$ with its value from equation (21) we obtain a single equation in α:

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

which can be rewritten as

$$
-F^{3122}\alpha^2 + F^{3113}\alpha + F^{1322} = 0, \tag{23}
$$

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 (23) 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 α and γ. 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 Lemma 1. **Part 1. Proof of equation (7) and (8).** 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

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

For the first equation, we have

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

where the equalities follow from Assumption 1. Similarly,

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

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

therefore

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

Similarly, we can verify the second equation:

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

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

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

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

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

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

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

Part 2. Proof of the equivalence between equations (7), (8) and equations (9) and (10)

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 (9),

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

which is equivalent to equation (7). Reorganizing equation (7) 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 (8) from equation (10). □

Proof of Corollary 1. Denote

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

$$\begin{aligned}
\phi_{Y,Z}(\zeta,\xi) &= E\left[\exp(i\zeta(U+V+e))\exp\left(i\xi\left(V + \frac{1}{\gamma-\alpha}R - \frac{\alpha}{\gamma-\alpha}e\right)\right)\right] \\
&= \phi_U(\zeta)\phi_V(\zeta+\xi)\phi_R\left(\frac{1}{\gamma-\alpha}\xi\right)\phi_e\left(\zeta - \frac{\alpha}{\gamma-\alpha}\xi\right) \qquad (24)
\end{aligned}$$

Let $\xi = 0$, we have

$$\phi_{Y,Z}(\zeta,0) = \phi_U(\zeta)\phi_V(\zeta)\phi_e(\zeta). \qquad (25)$$

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

$$\phi_{Y,Z}(0,\xi) = \phi_V(\xi)\phi_R\left(\frac{1}{\gamma-\alpha}\xi\right)\phi_e\left(-\frac{\alpha}{\gamma-\alpha}\xi\right) \qquad (26)$$

Multiplying equations (24)-(26) 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 α and γ 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 the independence assumption, 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 $0 \leq l < 3+p$, we have

$$\kappa_{Y,W}^{3+p-l,l+1} = \left[\frac{\partial^{3+p+1}\Phi_{Y,W}(\zeta,\xi)}{i^{3+p+1}\partial\zeta^{3+p-l}\partial\xi^{l+1}}\right]_{\zeta=0,\xi=0}$$
$$= \sum_{i=1}^{K}\alpha_i^{l+1}\kappa_{U_i}^{4+p} + \gamma^{l+1}\kappa_V^{4+p}. \tag{27}$$

Equation (27) implies that

$$\kappa_{Y,W}^{3+p,1} = \sum_{i=1}^{K}\alpha_i\kappa_{U_i}^{4+p} + \gamma\kappa_V^{4+p}, \tag{28}$$

$$\kappa_{Y,W}^{2+p,2} = \sum_{i=1}^{K}\alpha_i^2\kappa_{U_i}^{4+p} + \gamma^2\kappa_V^{4+p}, \tag{29}$$

$$\kappa_{Y,W}^{1+p,3} = \sum_{i=1}^{K}\alpha_i^3\kappa_{U_i}^{4+p} + \gamma^3\kappa_V^{4+p}. \tag{30}$$

In addition,

$$\kappa_Y^{4+p} = \sum_{i=1}^{K}\kappa_{U_i}^{4+p} + \kappa_V^{4+p} \tag{31}$$

Observe that:

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

Therefore, equation (12) can be established using relations (28) - (31) by eliminating all of $\kappa_{U_i}^{4+p}$ and κ_V^{4+p}.

A finite set of moment constraints can be constructed from equation (12). 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 Θ 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. □

B 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

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

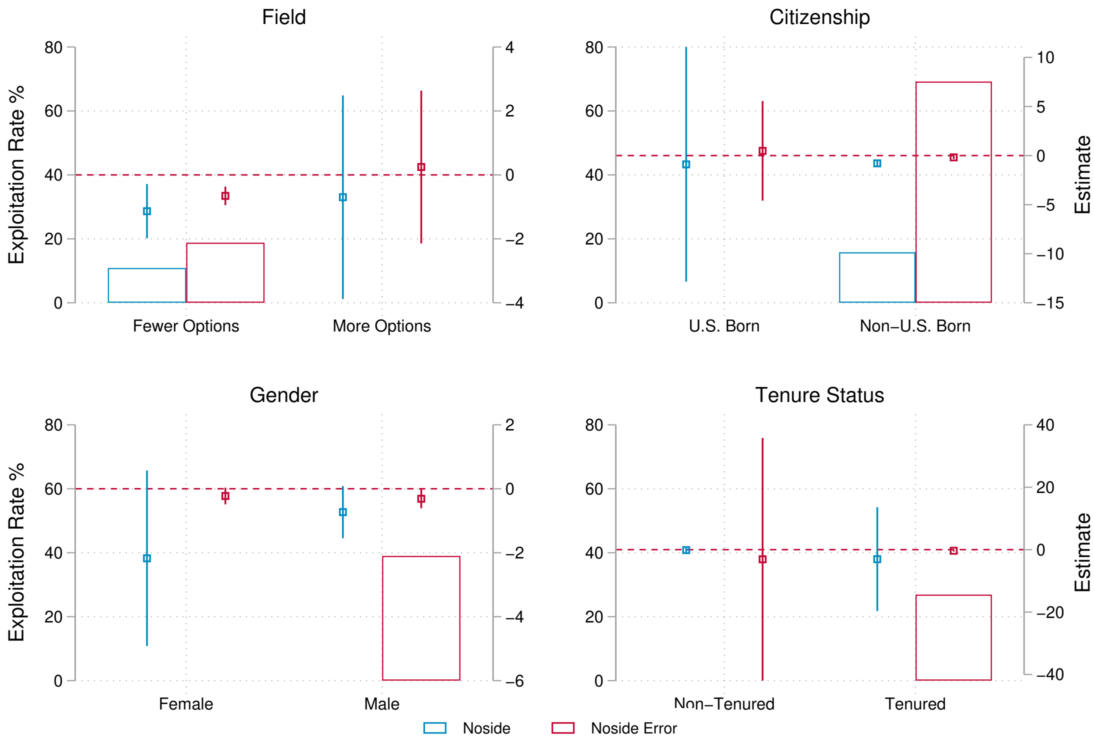
We get the additional moments:

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

and

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

C Appendix Figures



C.1: Monopsony Power Across Groups

Notes: This figure plots the estimates of γ and their 90% confidence intervals, based on robust standard errors, using both the LSZ method (shown in blue) and the LSZ error 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 γ is not statistically significant at conventional levels.

D Appendix Tables

D.1: Results from the University of California: Comparing 2SLS, LSZ, and LSZ-error

	2SLS (1)	LSZ (2)	LSZ-error (3)
β	-0.760*** (0.0805)		
γ		-0.343*** (0.0460)	-0.395*** (0.0652)
N	8089	8089	8089
Labor Supply Elasticity	15.144	6.829	7.865
Exploitation Rate	0.066	0.146	0.127

Notes: 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 (β), 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). In Columns (2) and (3), we report the LSZ and LSZ-error estimates (γ), respectively. 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.