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

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Abstract

We extend the linear triangular structural model considered in Lewbel, Schennach, and Zhang (2024) to allow for measurement errors in the endogenous regressor. We show identification of the causal effect and distributions of unobservables using higher-order moments of variables when instrumental variables or repeated measurements are not available. 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. We find evidence of monopsony, with the exploitation rate—a common measure of monopsony power—robustly estimated at 36%. Our analysis shows that ignoring measurement error would significantly underestimate monopsony power.

Keywords: Triangular System, Endogeneity, Measurement Error, Identification, Monopsony, Labor Market
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1 Introduction

A linear regression model containing endogenous regressors is generally identified using exclusion restrictions – by finding an instrumental variable that correlates with the endogenous regressor but not with errors in the outcome equation. However, valid instruments may not be available in some empirical settings. This led to the development of a range of approaches dealing with endogeneity in linear regression models not relying on exclusion restrictions (see Rigobon (2003), Klein and Vella (2010), and Lewbel (2012), among others). A recent development is Lewbel, Schennach, and Zhang (2024). In particular, they consider a triangular two-equation system where the endogeneity arises from a common unobserved factor, and obtain identification using higher moment restrictions rather than instruments.

One key assumption in Lewbel, Schennach, and Zhang (2024) (which we will hereafter refer to as LSZ) is that the common unobservable (the confounder) is a scalar.[1] This is not an innocuous restriction, given that empirical research often involves contaminated measures of the true variable.[2] In returns to schooling models, for example, researchers often concern that unobserved ability simultaneously impacts both educational attainments and future earnings. Assuming a scalar common latent variable implies that unobserved ability alone generates error correlations, which precludes the possibility of measurement error in the endogenous regressor. As noted by Card (2001), many returns to schooling empirical applications yield downward biased OLS estimates, likely driven by an attenuation bias from measurement error in addition to the upward bias from the unobserved ability. In fact, measurement error has been documented for self-reported educational attainment (see Black, Sanders, and Taylor (2003)).

What this paper shows is that the coefficient of a mismeasured endogenous regressor can still be identified without using instruments, under the assumption that the measure-

[1]We use "common latent variable", "common unobservable" and "confounder" interchangeably.

[2]As LSZ points out in their Appendix, the discrepancy between estimates using their proposed moments and the ones from valid IV moments is likely due to ignoring measurement error in the endogenous regressor.

ment error is independent of other latent variables with unknown distributions. As in LSZ, we assume mutual independence of all error components in the triangular structural model and use the implied moment constraints. Relaxing the single common factor assumption introduces challenges because, unlike LSZ, we have an additional unobservable showing up in both equations of the triangular system. We therefore require a different set of covariance information and relations of higher-order joint characteristic functions. This paper's identification results are most useful in cases where the primary interest lies in the causal effect (the slope coefficient). If the unknown distributions of latent variables are of particular interest, we show that they are point identified under extra assumptions about the distribution of the measurement error.

We further show identification of a more general model with a vector of common latent variables, of which measurement error is a special case. This generalization is relevant in empirical contexts where there may exist multiple confounders and each contributes to the error correlations differently. Even with multiple latent variables, estimation is standard in that we can directly construct GMM estimators based on easy-to-implement low order moments. Furthermore, we provide useful overidentifying moments to obtain more precise estimates than with exact-identifying moments.

Our identification is useful in settings where the structural model motivated by economic theory points to more than one factor generating endogeneity, and where traditional instruments are weak or not available. Even in cases where the common unobserved component is a scalar, our moments are applicable. When ordinary instruments are available, higher 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, which involves a model relating 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. Furthermore, salaries are subject to measurement errors due to reasons including non-reported compensation such as research grants, unaccounted benefits, stipends, and overtime pay, and errors arising from timing mismatches for quitters and 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. Except for the aforementioned applications, a mismeasured endogenous regressor can appear 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. Using LSZ's method in such settings contradicts the modeling assumption and is thus problematic.

More generally, in many cases, the unobservables consist of multiple latent variables. 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 be various things: CEO ability, development strategies, innovation, etc.

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

This paper is related to literature on using higher moments to identify error-in-variable model (Cragg (1997) and Dagenais and Dagenais (1997)). These models can be viewed as a special case of ours with restrictions on model parameters. In particular, they omit the important element of endogeneity from the unobserved common factor. Therefore, our identification is not a direct extension of these studies and requires different techniques.

There is a long literature considering both endogeneity and measurement error in nonlinear models or models with a binary endogenous regressor (see, for example, Song, Schennach, and White (2015), Hu, Shiu, and Woutersen (2015), and Ura (2018)). These papers typically rely on repeated measurements or instruments (or conditional variables) to handle both, while we consider empirical settings where such side information is not available, so their methodologies do not apply.

1.3 Monopsony Power in University System of Georgia. There has been burgeoning interest about the monopsony power since 2010.[3] 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 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 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 educa-

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

tion 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 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).[4] 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 the administrative salary data and faculty characteristics we scrapped online that spans from 2010 to 2022. This dataset is unique and has not been used in other studies. The newly acquired information on faculty attributes provide much more observed covariates we can condition on than previous studies. 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

[4]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*".

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 and that its magnitude differs from the findings in a blue state, as identified in previous research. Moreover, we demonstrate that its intensity varies over time, 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

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

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

with U, V, R being 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 classical measurement error, and maintain the other assumptions in LSZ, so U, V, R and e are mutually independent and mean zero.

In returns to schooling models, W represents wages and Y is schooling, with U capturing the individual's unobserved ability, and e is a 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 fails to hold without additional assumptions. Even if we assume U, V, R and e are mutually independent, observe that $E[(W-\gamma Y)(W-\gamma Y-\beta Y)Y] = E(\alpha\gamma e^3)$, which is nonzero unless we assume that the distribution of e is symmetric, i.e., $E(e^3) = 0$. Similarly, it requires $E(e^4) = 0$ for moment constraint (8) in Lemma 1 in LSZ to be satisfied. In the general identification theorem, for higher order moment conditions in LSZ continue to hold, all cumulants of e with order greater than two have to be zero. Such distributional assumptions are unlikely to be satisfied in practice. For example, asymmetric measurement errors are 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), we have

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

We show 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 we use 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 log of marginal characteristic functions (which is also called second characteristic function or cumulant generating function) and $\Phi_{Y,W}(\zeta,\xi) \equiv \ln E(\exp(i\zeta Y + i\xi W))$ denote 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

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

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

The proof is in the Appendix A. Intuitively, the mutual independence assumption allows us to express the joint characteristic function as products of marginal characteristic function. This enables joint cumulants across different orders (essentially different mixed covariances) to be represented as an additively separable function in the marginal cumulants of unobserved variables of the same orders.

Next, we use the relations between cumulants and moments[5] to derive low order moments to be used in constructing GMM estimators.

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

Lemma 1. *The following two moment constraints hold:*

$$
\begin{aligned}
&cov[(W-\gamma Y)(W-\alpha Y), YW] = \\
&\qquad E\left(WY-\gamma Y^2\right)E\left(W^2-\alpha YW\right)+E\left(W^2-\gamma YW\right)E\left(WY-\alpha Y^2\right) \qquad (7)\\
&cov[(W-\gamma Y)(W-\alpha Y), Y^2W] = \\
&\qquad 2E[(W-\gamma Y)Y]E[(W-\alpha Y)YW]+2E[(W-\alpha Y)Y]E[(W-\gamma Y)YW] \\
&\qquad +E(Y^2)E[(W-\gamma Y)(W-\alpha Y)W]+E(YW)E[(W-\gamma Y)(W-\alpha Y)Y] \\
&\qquad +E[(W-\gamma Y)W]E[(W-\alpha Y)Y^2]+E[(W-\alpha Y)W]E[(W-\gamma Y)Y^2]. \qquad (8)
\end{aligned}
$$

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

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

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

It gives two equations in two unknowns α and γ. Assume that $\alpha > \gamma$, from the moment restrictions in Lemma 1 we can point identify α and γ. In the empirical application, we provide results using moment restrictions up to $g_2(\alpha,\gamma) = 0$ to increase estimation precision. The full expression of this higher moment is provided in the Appendix B.

Note that Theorem 1 and Lemma 1 hold with distributions of U, V, R and e being unknown. We next consider identification of distributions of these variables.

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.*

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. The independence assumptions of Kotlarski's identity fail to hold due to the presence of e (with different slope coefficients) in both Y and $(W-\alpha)/(\gamma-\alpha)$ equations. In particular, without further restrictions, distributions of unobservables are not point identified when only Assumption

1 holds. To retrieve identification of U, V and R, we impose the extra assumption that the distribution of e is known and obtain Kotlarski's identity with an extra term. Even though assuming a known distribution for e may be a strong requirement, it can be satisfied in certain practical contexts. Consider the case where the true measure of the regressor is unobserved in the main sample, and there exists a second sample where both the contaminated measure and the true measure are observed. Suppose measurement errors in the two samples have 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, this assumption serves the role of scale normalization. One can first normalize the variance of e to a known constant, and the variance and skewness of the other unobservables can then be estimated along with α and γ.

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 $\{U_1 \dots U_K\}$ be a set of unobserved factors 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 above degenerates to the model considered in LSZ. In other words, assuming a scalar common latent variable is equivalent to assuming that all unobserved common factors impact the outcome variable to the same extent.

The general model is suitable for a lot of empirical work. 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 be various factors, including CEO ability, development strategies, innovation, etc.

We next 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 (11) hold. Let*

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

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

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

Let Θ be a bounded set and $\theta \equiv (\alpha_1,\ldots,\alpha_K,\gamma) \in \Theta$. Define a mapping $F(\theta):\Theta \longrightarrow F(\Theta)$ 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 Θ.

Proof is in Appendix A. Higher-order relations of cumulants of observed and unobserved variables are used to establish equation (12). These moment constraints can then be used to identify $\{\alpha_1,\ldots,\alpha_K,\gamma\}$ under rank conditions that guarantee a unique solution. More specifically, identification is achieved by applying a version of Hadamard's global inverse function theorem. Other studies using similar arguments to establish global identification include Chernozhukov and Hansen (2006) and Han and Vytlacil (2017). To see what the assumptions entail, take the mismeasured endogenous regressor model in the previous section as an example. 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 space $F(\Theta)$ is simply connected implies that it is path-connected and every loop within the space can be continuously contracted to a single point without leaving the space. In other words, there are no "holes" in the space. This corresponds to the assumption 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 in practice.

Even with the coefficients identified, distributions of unobservables are generally not point identified given that the number of unknown variables is far greater than the number of observed variables.[6] However, like in Corollary 1, one could characterize these distributions 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 $\phi_R(\xi) = f_R(\xi)\exp(P_K(\xi))$.*

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.

[6] As shown in Rao (1971), under the framework of model (11) with known coefficients, the joint distribution of two observed variables (Y, W) identifies the distributions of at most three unobserved variables up to location.

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:

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

along with

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

where $\mu_{\tilde{y}\tilde{w}}$ and $\mu_{\tilde{y}\tilde{y}\tilde{w}}$ are parameters estimated along with $(\gamma, \beta, \delta, \tau)$.

3 Application: Monopsony in Academia

In this section, we evaluate monopsony power in the academic labor market for a public university system that experienced 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 to estimate the wage elasticity of separations, labor supply elasticity, and the exploitation rate—a common measure of monopsony power. Next, we discuss challenges in the empirical analysis, including the endogenous and mismeasured salary variable, and the lack of commonly used salary scale instruments (IVs) for the endogenous regressor, which makes it a well-suited example illustrating the application of our method. We then describe the data and present the estimation results, comparing them with those from 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.[7] Solving Equation (15), we obtain the following key relationship,

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

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., $w = \mathrm{MRP}$. Alternatively, if $\varepsilon = 5$, the rate of exploitation rate is 20% and the university pays faculty

[7] 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.

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 attributes, work experience, educational background, and research ability. These variables are defined and discussed in detail in the Data section (see Section 3.2).

Salaries are widely acknowledged as endogenous in the separation equation. They are simultaneously determined by labor demand and supply. 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, we can write the observed salaries (denoted as $\ln Salary_i$, which is measured in logarithm) 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 becomes:

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

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.[8] Plugging the observed salary function back into the separation equation, the model becomes:

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

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

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

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.[9] 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 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.[10]

We control for faculty attributes including job title ($Title$), field of specialization

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

[10]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.

($Field$), gender ($Female$), and citizenship ($ForeignBorn$).[11] 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.[12]

Table 1 summarizes descriptive statistics of the outcome variable $Separation$, the 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. 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. Excluding these observations leads to a final use data with the sample size of 3002. The attrition rate is about 30%.

[11]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.

[12]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.

3.3 Results

We start by estimating Equation (18) using the method of Lewbel, Schennach, and Zhang (2024) (henceforce LSZ estimator) and the method developed in this paper (henceforce 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 concern, the OLS estimates of γ are in general small in magnitude, although they are statistically different from zero. They imply small labor supply elasticity and hence overestimate the exploitation rate. For example, from our preferred model with a full set of controls, the labor supply elasticity is only estimated at 0.69. 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 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 shows that the estimated labor supply elasticities in Panel B are likely overstated, which consequently underestimated the exploitation rate. 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. Compared to universities with higher levels of transparency in pay determination, such as the University of California (UC) system, monopsony power among the three USG institutions is significantly higher, at 36% versus 7% in the UC system (Yu and Flores-Lagunes 2024). 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 suggest that other aspects of transparency in compensation, such as transparent standardized salary scales, might also contribute to reducing pay compression.[13]

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.[14] 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.[15] While these revisions aimed to increase faculty accountability, they also raised concerns about academic freedom and tenure security, likely contributing to higher faculty separations. This trend of declining monopsony power might have con-

[13]The results of our study should not be interpreted as causal evidence of the impact of compensation transparency on monopsony power in academia. The influence of institutional patterns and faculty governance policies on monopsony could be a fruitful area for future research.

[14]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 suggests a sizable 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.

[15]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.

tinued 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.

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 B.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.[16] 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 and mitigate underestimation of monopsony power.

[16]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.

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-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.

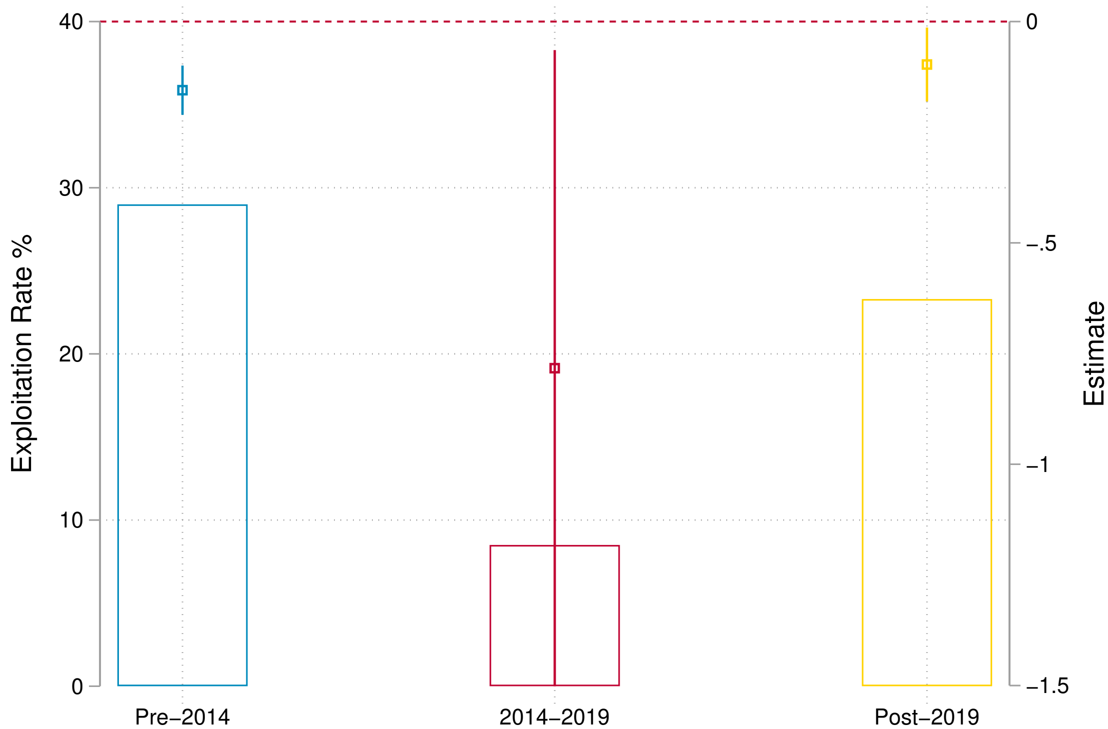

Figure 1: Trends in Monopsony Power

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**

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

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

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

and

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

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

therefore

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

Similarly, we can verify the second equation:

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

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

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

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

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

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

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

Part 2. Proof of the equivalence between equations (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),

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

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). $\square$

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

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

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:

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

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

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

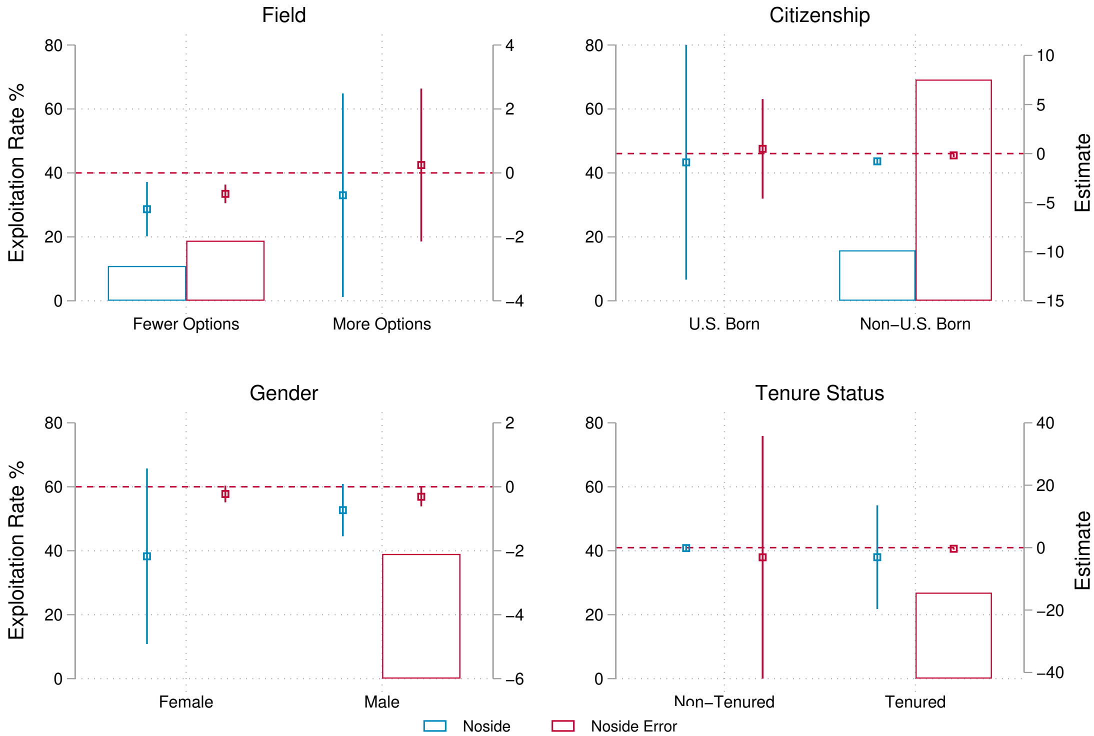
We get the additional moments:

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

and

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

C Appendix Figures



B.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.