Appendix A: Estimating the public-private sector pay gap

An often-used methodology to study labor-market outcomes by groups (sex, race, and so on) is to decompose mean differences in log wages based on linear regression models in a counterfactual manner. The procedure is known in the literature as the Blinder-Oaxaca decomposition (Blinder 1973[1]; Oaxaca 1973[2]). It divides the wage differential between two groups into a part that is "explained" by group differences in productivity characteristics, such as education or work experience, and a residual part that cannot be accounted for by such differences in wage determinants. This "unexplained" part is often used as a measure for discrimination, but it also subsumes the effects of group differences in unobserved predictors.

Given are two groups, A and B; an outcome variable, Y; and a set of predictors. For example, think of a group of public sector workers and a group of private sector workers, (log) wages as the outcome variable, and human capital indicators such as education and work experience as predictors. The question now is how much of the mean outcome difference is accounted for by group differences in the predictors.

Using the American Community Survey (ACS), we restrict our sample to males, heads of households, prime-working age (25-55) only. Annual wages and weekly hours are used to construct hourly wages. The wage data is split into deciles in order to eliminate extreme values at both ends of the distribution.

Figure 1: Decomposing wage differentials between non-college educated public and private sector workers in Illinois

Occupation	Total difference	Unexplained	Explained	Public sector pay higher/lower
Management, professional and related occupations	0.019	0.021	-0.002	Higher
Service occupations	0.415	0.403	0.012	Higher
Sales and office occupations	0.151	0.119	0.032	Higher

Figure 2: Decomposing wage differentials between college educated public and private sector workers in Illinois

Occupation	Total difference	Unexplained	Explained	Public sector pay higher/lower
Management, professional and related occupations	0.081	0.109	-0.028	Lower
Service occupations	0.473	0.467	0.006	Higher
Sales and office occupations	0.01	0.005	0.005	Higher

Appendix B: The effect of the public sector on unemployment

The empirical methodology and the exposition are taken from Behar and Mok (2013[3], 2015[4])

In order to explore the existence of crowding out, we estimate the following equation:

$$U_{i,t} = \beta_u Public_{i,t} + \gamma_u X_{i,t} + v_i + \theta_t + \varepsilon_{i,t}$$

The subscripts i and t identify the country and the period, respectively. $U_{i,t}$ is the unemployment rate, $Public_{i,t}$ is the public sector employment rate, $X_{i,t}$ is the vector of control variables which we discuss below, v_i is the state fixed effects, θ_t is the year effects and $\varepsilon_{i,t}$ is the residual.

If the coefficient β_u is close to -1, we can say that additional public jobs are purely accounted for by a fall in unemployment, which means that there is no net flow of workers from the private sector to the public sector and, hence no crowding out. If $\beta_u < -1$, then public employment also generates private sector jobs, or crowding in.

If β_u is between 0 and -1, it means some private-sector jobs are lost, but fewer than the number of public jobs created, so there is partial crowding out. If β_u is close to 0, it means there is no change in unemployment because job creation in the public sector

is completely cancelled by private sector job losses, which means full crowding out. If it is larger than 0, then crowding out effects are so strong that overall unemployment rises and there is more than full crowding out.

We control for demographic factors. We use year and state fixed effects. The right-hand side of our regressions has public employment rates that are likely to be correlated with state-specific but time invariant unobservable characteristics. If those characteristics affect the unemployment rate or private sector employment, it is important to eliminate those sources of bias.

One potential concern is that public hiring may respond to labor market conditions. For example, public hiring may increase during periods of slack private sector labor demand. Therefore, any relationship between public and private hiring may reflect a rise in the former taking place in response to a fall in the latter. In a statistical sense, this can lead to biased estimates of the causal effect of public employment on unemployment rates. To the extent that private employment is low because of long-term structural factors, this source of endogeneity is expunged by the use of fixed effects. To the extent that private sector labor demand is lower during periods of weak economic activity, this is controlled for by the GDP growth rate. To the extent that changes in labor freedom over time may affect private sector hiring for a given level of economic activity, this is controlled for by changes in the EFNA labor market freedom score.

In addition to standard fixed effects regressions, we also use Generalized Method of Moments (GMM) estimations, also known as Generalized Instrumental Variables (GIV), in a static framework (Cameron and Trivedi, 2005).[5]

In all regressions, public employment is positively correlated with the unemployment rate while labor market freedom is negatively correlated with unemployment. Results from our GMM estimations show that a 1 percentage point increase in the public employment rate is associated with a 0.2 percentage point increase in the unemployment rate. On the other hand, a 1 percentage point increase in the labor market freedom score is associated with a 0.6 percentage point decrease in the unemployment rate.

Unemployment rate regressions

Variables	(1)	(2)	(3)	(4)	(5)
Public employment rate	0.80 ***	0.68 ***		0.20 ***	
	(13.38)	(10.98)		(6.62)	
GDP Growth rate		-0.1 ***	-0.1 ***	-0.17 ***	-0.17 ***
		(-9.89)	(-9.89)	(-10.92)	(-12.52)
EFNA Labor Market Freedom score			- 0.42 ***		-0.63 ***
			(-6.79)		(-20.04)
Observations	1800	1750	1750	1750	1750
R-squared	0.81	0.82	0.81		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
All regressions contain a constant term and are estimated with year-specific effects.

In columns 1,2,3 we use the within-groups estimator.

In column 4 and 5, GMM is used where public employment/labor freedom score and GDP growth are treated as endogenous.

All regressions include demographic controls for 5 age groups, race, gender

[1] Blinder, A.S., "Wage discrimination: reduced form and structural estimates," *Journal of Human resources*, 436-455, (1973).

[2] Oaxaca, R., "Male-female wage differentials in urban labor markets," *International Economic Review*, 693-709, (1973).

[3] Behar, A., and Mok, J., "Does Public-Sector Employment Fully Crowd Out Private-Sector Employment?", *The International Monetary Fund,* Working Paper No. 13/146 (2013).

[4] Behar, A., and Mok, J., "Does Public Employment Reduce Unemployment?", *Topics in Middle Eastern and African Economies*, Vol. 7(2) (2015).

[5] Cameron, A. C., and Trivedi, P. K., "Microeconometrics: methods and applications," *Cambridge University Press*, (2005).