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Supplementary information

The influence of pay transparency on (gender) inequity, inequality and the performance basis of pay

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Supplementary materials for: The influence of pay transparency on (gender) inequity, inequality, and the performance-basis of pay

S1

Supplementary Table 1.1. Salary and employment data coverage by state.

State	First year in the data	Last year in the data
WV	2004	2017
VA	2003	2017
TX	1997	2017
PA	2003	2017
NY	2004	2016
FL	1997	2017
CT	2003	2017
CA	1998	2017

Productivity measures

For each individual, yearly productivity measures specify the cumulative output beginning in 2004 up to the year of analysis. We specify the following measures of academic output: number of academic articles in peer-reviewed journals, number of published books, number of academic awards, number (or value) of grants, and number of patents.
One of the crucial outcome variables in many disciplines is the number of publications in peer-reviewed academic journals. We only observe the number of such publications – a measure that could mask important quality heterogeneity. We therefore also collected data on all reported impact factors of journals in which articles in our sample were published. We then substitute the measure of a count of academic articles with JIF-weighted measures. We also constructed an impact measure captured with citations. However, we only observe the exact count of SSI citations from 2010 onwards. Based on this data, we imputed the number of citations in prior years imposing either a linear or exponential trend on the path of citation accumulation, starting with the year a PhD degree was obtained or a first academic publication is observed. However, given an extremely high ($\rho > 0.9$) correlation between the number of articles and citations, we cannot include both of these productivity measures in the same model. We report models with number of articles, as these do not rely on imputed values. Results including citations are qualitatively identical and available from the authors. In terms of awards, our measure includes major scientific awards such as the Fields Medal or the Nobel Prize but also field-specific and journal awards. The full list of awards and journals is available from the authors. We yearly winsorize all productivity outcomes at 1 and 99% to account for outliers. Finally, we measure academic tenure as (ln) number of years since graduation from a PhD program.

Descriptive statistics and academic disciplines

Supplementary Table 1.2. Summary statistics.

Variable	Mean (mode) [s.d.] yearly	Mean (mode) [s.d.] cumulative
Salary (ln)	11.39 (11.46) [0.69]	
Academic tenure (ln)	2.68 (2.83) [0.88]	
Academic Articles	1.63 (0) [3.10]	8.88 (1) [19.62]
Patents	0.02 (0) [0.13]	0.09 (0) [0.58]
Books	0.07 (0) [0.32]	0.40 (0) [1.34]
Grants (#)	0.08 (0) [0.33]	0.54 (0) [1.49]
Awards	0.03 (0) [0.16]	0.15 (0) [0.50]

Supplementary Table 1.3. Representation of academic domains in the data (11 categories).

Academic domain	% of observations in the data
Humanities	19.31
Physical and Mathematical Sciences	15.82
Biological and Biomedical Sciences	15.12
Social and Behavioral Sciences	14.12
Engineering	11.22
Family, Consumer, and Human Sciences	6.36
Business	5.54
Health Profession Sciences	5.15
Education	4.07
Agricultural Studies	1.90
Natural Resources and Conservation	1.39

Notes: We observe academic field for 59,616 individuals. For the remaining individuals, we specify the residual academic field category as “Other.” We re-run all our analyses dropping these individuals from our data and find qualitatively identical results. Percentages presented in the table are calculated with the ‘Other’ category omitted.

S2

Context: Public University system wage transparency in the US

Although salary information of the employees in the public university system in the US has historically been partially a matter of public record since the Freedom of Information Act in 1967 and a series of subsequent Sunshine Acts, in practice such transparency laws were highly restrictive, imposed significant costs on individuals interested in obtaining data, and varied greatly from state to state and from institution to institution. For example, Mas (*10*) reports difficulties encountered by journalists in California trying to gather salary data for employees of the public institutions. Similarly, a journalist from the Michigan Capital Confidential, reports a large fee requested by one of the Michigan universities in return for compiling salary data (*S1*). Jan Murphy and the Patriot News Company’s 2002 request for salaries of the PSU employees found its conclusion only five years later in the 2007 Supreme Court of Pennsylvania ruling in favor of releasing this information (PENNSYLVANIA STATE

UNIVERSITY v. Jan Murphy and the Patriot-News Company, Intervenors), although the earliest court decision that we could identify in favor of releasing individual salary information dates back to 1979 (Penokie v. Michigan Technological University). In soliciting and obtaining data for this paper, we also faced significant difficulties and heterogeneous policy interpretations in approval of our FOIA requests and access to historical wage data.

In the last decade, wage transparency in the public sector has been significantly facilitated by an emergence of searchable datasets developed and launched by newspapers, NGOs, and state agencies. Although in many cases it was technically possible to access some salary information prior to the launch of these public repositories, the individual-level costs were often prohibitive and, in many cases, entailed costly action. Therefore, following the launch of such aggregator websites, access to, and public discussion of salaries drastically increased. One indication of the intensity of these shocks can be seen from the web traffic generated by the databases. The Sacramento Bee's UC's salary database had over 6 million hits in the first two months since its launch (https://theaggie.org/2008/05/07/the-sacramento-bees-database-causes-upset/). Launching of this website has been used as a pay transparency shock by Card and colleagues (*22*). Similarly, just after its launch "the [Ohio salary] database was averaging about 300 searches a minute […], or a total of 200,000 searches in a day. Normally, it takes the organization about a month to log 200,000 data searches." (https://www.cleveland.com/metro/2011/08/ohio_treasurers_office_new_sal.html). The websites also generated a lot of discussion with newspaper headlines running titles like: "Texas Tribune's Public Employee Pay Database Taking Some Heat" (Dallas Magazine), "University profs: Scott posting of salaries part of 'attack'" (Herald-Tribune) and "Virginia wants to strip names from salary database" (Daily Press).

As discussed in the main body of the paper and as listed below, we limit our analyses to employees in eight states: California, Connecticut, Florida, New York, Pennsylvania, Texas, Virginia and West Virginia. While FOIL requests were filed with all relevant institutions in 50 states, due to data availability, legal structure or digitalization constraints, we restrict our analyses to these eight states. The exclusion of 42 states was driven by the following criteria. First, the 2013 Supreme Court of the United States' decision (McBurney v. Young, 569 U.S. 221) affirms the right of the States to limit FOIA application to state citizens. As non-citizens, we were denied data from some of the states. In several cases, we were denied access to information on the grounds that historical individual salary data are not public records. Second, for identification purposes, we excluded all states that could not provide us with data spanning at least 3 years prior to transparency shocks. Under FOIA laws, institutions are not obligated to create records that do not exist at the time of the request. Third, we excluded states in which data gathering would have been prohibitively costly. In several cases, institutions agreed to release the data but at a cost that exceeded possible budget. We also excluded states for which relevant obtained information was not available in a digital format and would have been excessively costly to digitize (e.g., paycheck scans with differing formats). Finally, some institutions did not respond to our requests or needed excessive delay time to procure the records. We also excluded institutions that were established less than 3 years prior to the transparency shocks. For each of the states in our sample, we gathered information about the formal launch of a first publicly accessible database as well as related press releases. Table S2.1 provides a summary of the shocks to pay transparency along with the associated releasing source. Importantly for our research design, these websites were launched in a staggered fashion between 2007 and 2012 across the eight states. Although the exact date of availability of salary data via these websites may have varied by institution, these public repositories had a dramatic state-wide effect on the transparency of pay and associated responses. Accordingly, they provide a natural set of shocks to pay transparency that we leverage in our empirical analyses.

Supplementary Table 2.1. Transparency shocks by state.

State	Website or Newspaper	Launch Year
WV	Wvcheckbook.gov	2007
VA	Richmond Times-Dispatch	2010
TX	Texas Tribune	2009
PA	Pennwatch.pa.gov	2012
NY	Seethroughny.net	2008
FL	Floridahasarighttoknow.myflorida.com	2011
CT	Transparency.CT.gov	2010
CA	The Sacramento Bee	2008

S3

Supplementary Table 3.1. The unconditional and conditional gender wage gap over time.

DV: ln(Wage)		(1)	(2)
		Unconditional Wage Gap	Conditional Wage Gap
Female		-0.231	-0.138
		(0.018)	(0.009)
Female X			
	1999	-0.018	
		(0.024)	
	2000	-0.025	
		(0.023)	
	2001	-0.016	
		(0.022)	
	2002	-0.003	
		(0.022)	
	2003	-0.016	
		(0.021)	
	2004	-0.035	
		(0.020)	
	2005	-0.022	0.008
		(0.020)	(0.013)
	2006	-0.010	0.017
		(0.019)	(0.012)
	2007	0.002	0.026
		(0.019)	(0.012)
	2008	0.011	0.040
		(0.019)	(0.012)
	2009	0.026	0.060
		(0.019)	(0.012)
	2010	0.023	0.061
		(0.019)	(0.012)
	2011	0.038	0.076

		(0.019)	(0.012)
	2012	0.029	0.068
		(0.019)	(0.011)
	2013	0.043	0.080
		(0.019)	(0.011)
	2014	0.058	0.082
		(0.019)	(0.011)
	2015	0.065	0.091
		(0.019)	(0.011)
	2016	0.073	0.096
		(0.019)	(0.011)
	2017	0.084	0.112
		(0.019)	(0.011)
Institution fixed effects		no	yes
Academic field fixed effects		no	yes
Year fixed effects		yes	yes
Productivity controls		no	yes
Observations		566,242	306,404

Notes: The table reports OLS regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of published academic articles, number of published books, number of awards, number of grants, and number of patents. Standard errors clustered at the level of institution in parentheses.

Supplementary Table 3.2. The effect of pay transparency on gender wage gap.

DV: ln(Wage)	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.060	0.034	0.006	-0.009	-0.009	-0.015
	(0.012)	(0.011)	(0.011)	(0.009)	(0.008)	(0.008)
Female		-0.211	-0.112	absorbed	-0.062	absorbed
		(0.018)	(0.009)		(0.005)	
Treatment # Female		0.067	0.059	0.031	0.020	0.021
		(0.011)	(0.008)	(0.004)	(0.005)	(0.004)
Associate Professor					0.121	0.064
					(0.008)	(0.007)
Full Professor					0.391	0.173
					(0.012)	(0.014)
Productivity controls	no	no	yes	yes	yes	yes
Individual fixed effects	no	no	no	yes	no	yes
Academic field fixed effects	yes	yes	yes	absorbed	yes	absorbed
Institution fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	676,055	556,242	306,404	300,853	195,976	194,077

Notes: The table presents OLS regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of academic articles, number of books, number of awards, number of grants, and number of patents. In models 5-6 omitted category is Assistant Professor. Standard errors clustered at the level of institution in parentheses.

To calculate state-level private sector wage gap used in estimating model reported in Panel C, Extended Data Figure 3, we use the Annual Social Economic Supplement of the IPUMS CPS (Current Population Survey) microdata (IPUMS-CPS, www.ipums.org). This data results from a joint effort between the Bureau of Labor Statistics and the Census Bureau, and provides the official US Government statistics on employment and wages. CPS ASEC reports stratified random samples where the U.S. is divided into 1,987 "primary sampling units" (PSUs), and these PSUs are grouped into homogenous strata within each state. Within the selected PSUs, a block of households is sampled and asked work-related questions for each member of the household 15 years of age or older as of a particular calendar week. In the supplementary dataset that we create for 2004-2017 period, there are 904,355 individual-year observations in the 8 states we examine. We exclude all those working in industries with its Census code greater than or equal to 9370 (thereby focusing only on private sectors) and those who reported to be unemployed, retired, or unable to work. After this adjustment, we are left with a working sample of 604,998 individual-year observations. To calculate the unconditional gender wage gap in the private sector, we look at the relative median income of men and female workers, by year and state. Our results are insensitive to using mean values.

Supplementary Table 3.3. Equity in organizations: The effect of pay transparency on gender wage gap.

	β, t_{df}, (s.e.), p-value, [95% CI]	
DV: ln(Wage)	(1)	(2)
	OLS	IV
Years from (to) transparency shock X Female		
(<3)	-0.016, t_{138}=2.91 (0.005), 0.004 [-0.03;-0.01]	-0.014, t_{138}=2.67 (0.005), 0.009 [-0.02;-0.00]
(3)	-0.001, t_{138}=0.19 (0.005), 0.849 [-0.01;0.01]	0.001, t_{138}=0.25 (0.004), 0.800 [-0.01;0.01]
(2)	-0.005, t_{138}=0.85 (0.005), 0.396 [-0.02;0.01]	Omitted
(1)	Omitted	Omitted
Shock	0.009, t_{138}=1.93 (0.004), 0.056 [0.00;0.02]	0.011, t_{138}=2.64 (0.004), 0.009 [0.00;0.02]
1	0.022, t_{138}=2.06 (0.011), 0.041 [0.00;0.04]	0.025, t_{138}=2.31 (0.011), 0.022 [0.00;0.05]
2	0.017, t_{138}=3.53 (0.005), 0.001 [0.01;0.03]	0.020, t_{138}=3.44 (0.006), 0.001 [0.01;0.03]
3	0.020, t_{138}=3.78 (0.005), <0.001 [0.01;0.03]	0.022, t_{138}=4.80 (0.005), <0.001 [0.01;0.03]
>3	0.035, t_{138}=5.78 (0.006), <0.001 [0.02;0.05]	0.037, t_{138}=6.56 (0.006), <0.001 [0.03;0.05]
Productivity controls	yes	yes
Individual fixed effects	yes	yes
Institution fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	300,853	300,853

Notes: The table presents OLS (model 1) and 2SLS (model 2) regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of academic articles, number of books, number of awards, number of grants, and number of patents. Standard errors clustered on institution in parentheses. In model 2, women's mean earnings as a % of men's in the private sector is the instrumented covariate and 1-year lead of transparency shock an excluded instrument.

Supplementary Table 3.4. Equity in organizations: The effect of pay transparency on gender wage gap. Stacked specification.

DV: ln(Wage)	
	β, t_{df}, (s.e.), p-value, [95% CI]
Years from (to) transparency shock X Female	
(3)	-0.007, t_{135}=0.71 (0.009), 0.477 [-0.03;0.01]
(2)	-0.003, t_{135}=0.41 (0.008), 0.680 [-0.02;0.01]
(1)	Omitted
Shock	0.016, t_{135}=2.24 (0.007), 0.027 [0.00;0.03]
1	0.026, t_{135}=1.79 (0.015), 0.075 [-0.00;0.06]
2	0.017, t_{135}=2.24 (0.008), 0.027 [0.00;0.03]
Productivity controls	yes
Individual fixed effects	yes
Institution fixed effects	yes
Cohort fixed effects	yes
Year fixed effects	yes
Observations	286,550

Notes: The table presents OLS regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of academic articles, number of books, number of awards, number of grants, and number of patents. Standard errors clustered on institution in parentheses. See text for more details on the stacking procedure.

Supplementary Table 3.5. Equity in organizations: The effect of pay transparency on gender wage gap. Restricted sample.

DV: ln(Wage)	
	β, t_{df}, (s.e.), p-value, [95% CI]
Years from (to) transparency shock X Female	
(5)	-0.005, t_{69}=0.99 (0.006), 0.327 [-0.02;0.01]
(4)	-0.015, t_{69}=1.74 (0.009), 0.086 [-0.03;0.00]
(3)	0.001, t_{69}=0.15 (0.006), 0.884 [-0.01;0.01]
(2)	-0.008, t_{69}=1.59 (0.005), 0.117

	[-0.02;0.00]
(1)	Omitted
Shock	0.008, t_{69}=1.54 (0.005), 0.128 [-0.00;0.02]
1	0.030, t_{69}=1.60 (0.018), 0.114 [-0.01;0.07]
2	0.014, t_{69}=2.25 (0.006), 0.028 [0.00;0.03]
3	0.024, t_{69}=3.73 (0.006), <0.001 [0.01;0.04]
4	0.022, t_{69}=3.38 (0.007), 0.001 [0.01;0.04]
Productivity controls	yes
Individual fixed effects	yes
Institution fixed effects	yes
Cohort fixed effects	yes
Year fixed effects	yes
Observations	166,587

Notes: The table presents OLS regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of academic articles, number of books, number of awards, number of grants, and number of patents. Standard errors clustered on institution in parentheses. Population restricted to academics employed in institutions located in the following states: CT, FL, PA, TX, VA.

Supplementary Table 3.6. The effect of wage transparency on gender pay gap: Mobility restricted sample.

DV: ln(Wage)	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.042	0.022	0.010	0.001	-0.002	-0.008
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.008)
Female		-0.200	-0.104	absorbed	-0.061	absorbed
		(0.019)	(0.008)		(0.005)	
Treatment # Female		0.064	0.045	0.030	0.022	0.020
		(0.010)	(0.006)	(0.004)	(0.005)	(0.004)
Associate Professor					0.104	0.067
					(0.010)	(0.007)
Full Professor					0.364	0.179
					(0.013)	(0.014)
Productivity controls	no	no	yes	yes	yes	yes
Individual fixed effects	no	no	no	yes	no	yes
Academic field fixed effects	yes	yes	yes	absorbed	yes	absorbed
Institution fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	375,865	316,040	212,032	211,682	153,396	153,003

Notes: The table presents OLS regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of academic articles, number of books, number of awards, number of grants, and number of patents. In models 5-6 omitted category is Assistant Professor. Sample is restricted by dropping all individuals who have: 1) changed institutions within our observation window but stayed in our working sample, (2) left our observation sample between the time of the transparency shock and 2017, or (3) joined our sample posterior to the transparency shock. Standard errors clustered at the level of institution in parentheses.

Supplementary Table 3.7. The effect of wage transparency on gender pay gap: Time restricted sample.

DV: ln(Wage)	(1)	(2)	(3)	(4)
Treatment	0.058	-0.010	0.092	0.005
	(0.016)	(0.009)	(0.025)	(0.013)
Female	-0.214	absorbed	-0.217	absorbed
	(0.018)		(0.018)	
Treatment # Female	0.050	0.023	0.050	0.025
	(0.011)	(0.003)	(0.011)	(0.006)
	Year restricted to < 2014		Year restricted to < 2012	
Productivity controls	no	yes	no	yes
Individual fixed effects	no	yes	no	yes
Academic field fixed effects	yes	absorbed	yes	absorbed
Institution fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	418,096	195,520	340,131	146,307

Notes: The table presents OLS regression estimates explaining (ln) salaries. Productivity controls include academic tenure (ln), number of academic articles, number of books, number of awards, number of grants, and number of patents. Standard errors clustered at the level of institution in parentheses.

S4

Supplementary Table 4.1. The effect of pay transparency on institution-academic field variance in market wage residuals.

DV: Variance in residual from market wage regression	(1)	(2)	(3)	(4)
Within:	Institution – academic field (11 categories)		Institution –academic field (25 categories)	
Treatment	-0.034 (0.015)	-0.034 (0.014)	-0.019 (0.009)	-0.019 (0.009)
Controls for mean productivity and variance in productivity	no	yes	no	yes
Institution-academic field fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	9,015	9,015	14,171	14,171

Notes: The table presents OLS regression estimates explaining institution-academic field variance in residual from market wage regressions. Wage regressions controls include academic tenure (ln), number of academic articles, number of published books, number of awards, number of grants, and number of patents and institution, academic domain, and year fixed effects. Residuals trimmed at 1% and 99%. Standard errors clustered at the level of institution in parentheses. In models 2 and 4 we include controls for average institution-academic field cumulative productivity outcomes and variance of these productivity outcomes.

Supplementary Table 4.2. The effect of pay transparency on institution-academic field variance in (ln) wages.

DV: Wage variance	(1)	(2)	(3)	(4)
Within:	Institution – academic field (11 categories)		Institution –academic field (25 categories)	
Treatment	-0.065 (0.015)	-0.068 (0.016)	-0.048 (0.014)	-0.055 (0.014)
Controls for mean productivity and variance in productivity	no	yes	no	yes
Institution-academic field fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	12,892	9,133	17,173	14,360

Notes: The table presents OLS regression estimates explaining variance in salaries. Standard errors clustered at the level of institution in parentheses. In models 2 and 4 we include controls for average institution-academic field cumulative productivity outcomes and variance of these productivity outcomes.

Supplementary Table 4.3. Equity and equality in organizations: The effect of wage transparency on variance in market wage residuals and wage variance.

	β, t_{df}, (s.e.), p-value, [95% CI]	
DV:	Variance in market wage residuals	Variance in (ln) wages
Within :	Institution – academic field (11 categories)	
Years from (to) transparency shock :		
(<3)	0.001, t_{130}=0.02 (0.035), 0.983 [-0.07;0.07]	-0.019, t_{131}=0.51 (0.038), 0.608 [-0.09;0.05]
(3)	0.017, t_{130}=0.84 (0.020), 0.402 [-0.02;0.06]	0.011, t_{131}=0.48 (0.022), 0.631 [-0.03;0.06]
(2)	0.031, t_{130}=2.30 (0.013), 0.023 [0.00;0.06]	0.018, t_{131}=1.15 (0.016), 0.252 [-0.01;0.05]
(1)	Omitted	Omitted
Shock	-0.021, t_{130}=1.30 (0.016), 0.195 [-0.05;0.01]	-0.057, t_{131}=3.81 (0.015), <0.001 [-0.09;-0.03]
1	-0.038, t_{130}=1.96 (0.016), 0.052 [-0.08;0.00]	-0.091, t_{131}=3.86 (0.024), <0.001 [-0.14;-0.04]
2	-0.043, t_{130}=2.46 (0.018), 0.015 [-0.08;-0.01]	-0.112, t_{131}=4.36 (0.026), <0.001 [-0.16;-0.06]
≥3	-0.068, t_{130}=2.61 (0.026), 0.010 [-0.12;-0.02]	-0.159, t_{131}=4.46 (0.036), <0.001 [-0.23;-0.09]
Institution-academic field fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Controls for mean productivity and variance in productivity	Yes	Yes
Observations	9,015	9,060

Notes: The table present OLS regression estimates explaining variance in market wage residuals (model 1) and variance in (ln) wages (model 2). Reference category is 1 year prior to transparency shock. Both variables are calculated within Institution-Academic Field (11 categories). Standard errors clustered on institution in parentheses. Controls include reference group mean productivity levels and reference group productivity variances.

S5

Supplementary Table 5.1. The effect of wage transparency on the determinants of pay.

DV: ln(Wage)	(1)	(2)	(3)	(4)	(5)
Treatment		0.0581 (0.0159)	0.0553 (0.0159)		0.0419 (0.0097)
Academic tenure (ln)	0.1492 (0.0144)	0.1405 (0.0148)	0.1407 (0.0149)		
Academic tenure (ln) # treatment		-0.0156 (0.0058)	-0.0168 (0.0058)		
Academic Articles	0.0010 (0.0001)	0.0022 (0.0004)	0.0005 (0.0001)		
Academic Articles # treatment		-0.0010 (0.0003)	-0.0003 (0.0001)		
Patents	-0.0032 (0.0023)	0.0071 (0.0047)	0.0134 (0.0052)		

	(1)	(2)	(3)	(4)	(5)
Patents # treatment		-0.0087	-0.0116		
		(0.0042)	(0.0046)		
Books	0.0046	0.0110	0.0119		
	(0.0013)	(0.0023)	(0.0023)		
Books # treatment		-0.0057	-0.0063		
		(0.0021)	(0.0021)		
Grants (#)	0.0139	0.0201	0.0246		
	(0.0016)	(0.0025)	(0.0028)		
Grants (#) # treatment		-0.0059	-0.0068		
		(0.0022)	(0.0025)		
Awards	0.0092	0.0024	0.0064		
	(0.0029)	(0.0042)	(0.0043)		
Awards # treatment		0.0073	0.0062		
		(0.0042)	(0.0042)		
Associate Professor				0.1147	0.1352
				(0.0069)	(0.0069)
Associate Professor # treatment					-0.0592
					(0.0079)
Full Professor				0.2478	0.2768
				(0.0125)	(0.0142)
Full Professor # treatment					-0.0690
					(0.0129)
Individual fixed effects	yes	yes	yes	yes	yes
Institution fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	364,301	364,301	364,301	333,828	333,828

Notes: The table presents OLS regression estimates explaining (ln) salaries. In model 3, we substitute a measure of count of the number of academic articles with Journal Impact Factor-weighted measure of academic output. Standard errors clustered at the level of institution.

Supplementary Table 5.2. The effect of wage transparency on the determinants of pay: Mobility restricted sample.

DV: ln(Wage)	(1)	(2)	(3)	(4)
Treatment		0.1102		0.0554
		(0.0133)		(0.0104)
Academic tenure (ln)	0.1556	0.1309		
	(0.0131)	(0.0126)		
Academic tenure (ln) # treatment		-0.0306		
		(0.0049)		
Academic Articles	0.0010	0.0023		
	(0.0001)	(0.0004)		
Academic Articles # treatment		-0.0011		
		(0.0003)		
Patents	-0.0047	0.0070		
	(0.0026)	(0.0056)		
Patents # treatment		-0.0099		
		(0.0048)		
Books	0.0058	0.0112		
	(0.0015)	(0.0022)		
Books # treatment		-0.0047		
		(0.0019)		
Grants (#)	0.0146	0.0208		
	(0.0017)	(0.0022)		
Grants (#) # treatment		-0.0058		
		(0.0020)		
Awards	0.0113	0.0036		
	(0.0036)	(0.0042)		
Awards # treatment		0.0082		
		(0.0047)		
Associate Professor			0.1087	0.1359
			(0.0075)	(0.0071)
Associate Professor # treatment				-0.0699
				(0.0086)
Full Professor			0.2366	0.2616
			(0.0139)	(0.0157)

Full Professor # treatment				-0.0614
				(0.0120)
Individual fixed effects	yes	yes	yes	yes
Institution fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	254,653	254,653	221,262	221,262

Notes: The table presents OLS regression estimates explaining (ln) salaries. Specifications as in Table S5.1. Sample is restricted by dropping all individuals who have: 1) changed institutions within our observation window but stayed in our working sample, (2) left our observation sample between the time of the transparency shock and 2017, or (3) joined our sample posterior to the transparency shock. Standard errors clustered at the level of institution in parentheses.

Supplementary Table 5.3a. The effect of wage transparency on the determinants of pay, by discipline.

DV: ln(Wage)	Population	Humanities	Physical and Mathematical Sciences	Biological and Biomedical Sciences	Social and Behavioral Sciences	Engineering
Academic Articles	0.002	0.003	0.002	0.003	0.003	0.002
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Academic Articles # treatment	-0.001	-0.000	-0.001	-0.002	-0.001	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Patents	0.007	-0.144	0.026	-0.003	0.001	0.014
	(0.005)	(0.257)	(0.007)	(0.008)	(0.083)	(0.005)
Patents # treatment	-0.009	0.205	-0.023	-0.002	-0.021	-0.005
	(0.004)	(0.250)	(0.008)	(0.005)	(0.059)	(0.005)
Books	0.011	0.017	0.003	-0.006	0.009	-0.001
	(0.002)	(0.003)	(0.006)	(0.008)	(0.003)	(0.005)
Books # treatment	-0.006	-0.007	-0.007	0.000	-0.006	-0.003
	(0.002)	(0.003)	(0.004)	(0.006)	(0.003)	(0.003)
Grants (#)	0.020	0.013	0.029	0.018	0.031	0.012
	(0.002)	(0.012)	(0.005)	(0.003)	(0.007)	(0.004)
Grants (#) # treatment	-0.006	0.005	-0.008	-0.004	-0.005	0.002
	(0.002)	(0.009)	(0.004)	(0.003)	(0.004)	(0.003)
Awards	0.002	-0.017	0.010	0.008	0.005	0.005
	(0.004)	(0.016)	(0.009)	(0.010)	(0.012)	(0.008)
Awards # treatment	0.007	0.030	0.007	-0.005	0.000	0.002
	(0.004)	(0.017)	(0.009)	(0.009)	(0.011)	(0.007)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Institution fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,301	71,253	58,015	56,476	51,598	41,124

Notes: The table presents OLS regression estimates explaining (ln) salaries. Standard errors clustered at the level of institution in parentheses.

Supplementary Table 5.3b. The effect of wage transparency on the determinants of pay, by discipline.

DV: ln(Wage)	Population	Humanities	Physical and Mathematical Sciences	Biological and Biomedical Sciences	Social and Behavioral Sciences	Engineering
Associate Professor	0.135	0.119	0.108	0.135	0.134	0.104
	(0.007)	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Associate Professor # treatment	-0.059	-0.049	-0.070	-0.074	-0.047	-0.065
	(0.008)	(0.009)	(0.014)	(0.012)	(0.016)	(0.014)
Full Professor	0.277	0.245	0.204	0.267	0.263	0.171
	(0.014)	(0.019)	(0.023)	(0.022)	(0.019)	(0.018)
Full Professor # treatment	-0.069	-0.037	-0.049	-0.074	-0.049	-0.043
	(0.013)	(0.012)	(0.019)	(0.015)	(0.017)	(0.021)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Institution fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	333,828	49,292	38,149	33,501	33,715	27,967

Notes: The table presents OLS regression estimates explaining (ln) salaries. Standard errors clustered at the level of institution in parentheses. Assistant Professor is the omitted baseline category.

Supplementary Table 5.4. The effect of wage transparency on salary adjustments associated with promotions.

	β, t_{df}, (s.e.), p-value, [95% CI]	
DV: ln(Wage)		
Years from (to) transparency shock X :	Associate Professor	Full Professor
(<3)	0.027, t_{89}=3.03 (0.009), 0.003 [0.01;0.04]	0.017, t_{89}=1.13 (0.015), 0.261 [-0.01;0.05]
(3)	0.020, t_{89}=2.89 (0.007), 0.005 [0.01;0.03]	0.012, t_{89}=1.37 (0.009), 0.173 [-0.01;0.03]
(2)	0.010, t_{89}=2.00 (0.005), 0.048 [0.00;0.02]	-0.001, t_{89}=0.24 (0.006), 0.814 [-0.01;0.01]
(1)	Omitted	Omitted
Shock	-0.028, t_{89}=5.27 (0.005), <0.001 [-0.04;-0.02]	-0.037, t_{89}=5.45 (0.007), <0.001 [-0.05;-0.02]
1	-0.042, t_{89}=4.99 (0.009), <0.001 [-0.06;-0.03]	-0.069, t_{89}=6.09 (0.011), <0.001 [-0.09;-0.05]
2	-0.032, t_{89}=4.97 (0.007), <0.001 [-0.05;-0.02]	-0.059, t_{89}=6.18 (0.009), <0.001 [-0.08;-0.04]
3	-0.039, t_{89}=5.04 (0.008), <0.001 [-0.05;-0.02]	-0.056, t_{89}=5.88 (0.010), <0.001 [-0.08;-0.04]
≥3	-0.078, t_{89}=6.92 (0.011), <0.001 [-0.10;-0.06]	-0.095, t_{89}=5.29 (0.018), <0.001 [-0.13;-0.06]
Institution, academic field fixed effects	Yes	

Year fixed effects	Yes
Observations	333,828

The table reports OLS regression estimates explaining (ln) salaries. Standard errors clustered at the level of institution in parentheses. Not reported but included in the regressions are uninteracted dummy variables for years to(from) transparency shocks and indicators for Associated and Full professors. Assistant Professor is the omitted baseline category.

Supplementary Table 5.5. The effect of market wage and pay transparency on yearly wage increases.

DV: % Wage change					
	Underpaid and overpaid: continuous specification		Underpaid and overpaid: binary specification		
	(1)	(2)	(3)	(4)	(5)
Treatment		-0.013		-0.157	-0.347
		(0.420)		(0.413)	(0.398)
Underpaid	2.857	2.329	1.372	1.028	0.766
	(0.466)	(0.501)	(0.155)	(0.221)	(0.173)
Underpaid # treatment		0.831		0.531	0.516
		(0.368)		(0.193)	(0.163)
Overpaid	-5.551	-5.193	-1.568	-1.582	-1.452
	(0.355)	(0.583)	(0.103)	(0.161)	(0.138)
Overpaid # treatment		-0.574		0.023	0.161
		(0.574)		(0.135)	(0.125)
Low salary					0.528
					(0.240)
Low salary # treatment					0.282
					(0.219)
Academic field fixed effects	Yes	Yes	Yes	Yes	Yes
Institution fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	261,100	261,100	259,624	259,624	259,624

Notes: $DV = \frac{Wage_{i,t+1} - Wage_{i,t}}{Wage_{i,t+1}} \times 100$. In the continuous specification, underpaid is defined as the absolute value of the individual *i*'s residual from regression predicting market wage in year *t* if the residual is negative and 0 otherwise. Overpaid is defined as the value of individual *i*'s residual from regression predicting market wage in year *t* if the residual is positive and 0 otherwise. In the binary specification underpaid is equal to 1 if individual *i*'s residual from regression predicting market wage in year *t* is negative and smaller than the average residual from the same regression for all individuals in a given year, the same institution and the same academic domain. Overpaid is equal to 1 if individual *i*'s residual from regression predicting market wage in year *t* is positive and greater than the average residual from the same regression for all individuals in a given year, the same institution and the same academic domain . *Low salary* is equal to 1 if individual *i*'s salary is below average, compared to year-institution-domain peers and 0 otherwise. Standard errors clustered at the level of institution in parentheses.

S6

Robustness tests: Exclusion of California and Texas.

Although our data spans eight states, the largest population of academics in our sample works in institutions located in California and Texas. Therefore one may be concerned that our results are driven by one of these states rather than represent a general pattern in the sample. Below we report results presented in Tables 1 and 2 excluding these states from our analyses.

Supplementary Table 6.1. Robustness of the effects of wage transparency on gender pay gap to exclusion of states.

DV: ln(Wage)	(1)	(2)	(3)	(4)
Treatment	0.026	0.018	0.005	-0.007
	(0.014)	(0.014)	(0.012)	(0.009)
Female	-0.115	-0.103	absorbed	absorbed
	(0.010)	(0.012)		
Treatment # Female	0.057	0.050	0.027	0.024
	(0.009)	(0.010)	(0.005)	(0.005)
Productivity controls	yes	yes	yes	yes
Individual fixed effects	no	no	yes	yes
Academic field fixed effects	yes	yes	absorbed	absorbed
Institution fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Omitted State	CA	TX	CA	TX
Observations	212,143	207,224	208,218	202,866

Notes: The table presents OLS regression estimates explaining (ln) salaries. Standard errors clustered at the level of institution in parentheses.

Supplementary Table 6.2. Robustness of the effects of wage transparency on institution-academic field variance in market wage residuals to exclusion of states.

DV: Variance in residual from market wage regression	(1)	(2)	(3)	(4)
Within:	Institution – academic field (11 categories)		Institution –academic field (25 categories)	
Treatment	-0.033	-0.051	-0.015	-0.026
	(0.016)	(0.020)	(0.011)	(0.012)
Controls for mean productivity and variance in productivity	yes	yes	yes	yes
Institution-academic field fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Omitted state	CA	TX	CA	TX
Observations	7,482	5,562	11,220	8,640

Notes: The table presents OLS regression estimates explaining variance in market wage residuals. Standard errors clustered at the level of institution in parentheses.

Supplementary Table 6.3. Robustness of the effects of wage transparency on pay variance to exclusion of states.

DV: Pay variance	(1)	(2)	(3)	(4)
Within:	Institution – academic field (11 categories)		Institution –academic field (25 categories)	
Treatment	-0.056 (0.018)	-0.087 (0.022)	-0.037 (0.015)	-0.076 (0.019)
Controls for mean productivity and variance in productivity	yes	yes	yes	yes
Institution-academic field fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Omitted state	CA	TX	CA	TX
Observations	7,591	5,668	11,387	8,786

Notes: The table presents OLS regression estimates explaining variance in salaries. Standard errors clustered at the level of institution in parentheses.

All standard errors reported in the paper are based on clustering at the institution level. Available from the authors are results based on clustering at the state-year and state level. Our results are robust to these alternative specifications. When clustering at the state level was used, due to few clusters, we performed wild bootstrap-based tests for testing hypotheses about the coefficients (Cameron et al., 2008; Djogbenou et al., 2019).

Additional references:

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S6. Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. "Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics* 90.3 (2008): 414-427.
Djogbenou, Antoine A., James G. MacKinnon, and Morten Ørregaard Nielsen. "Asymptotic theory and wild bootstrap inference with clustered errors." *Journal of Econometrics* 212.2 (2019): 393-412.