Mind the Gap: Public and Private Sector Wages in Turkey

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February 28, 2014

Abstract

The wage gap between public sector and private sector workers is important for both labor market dynamics and efficiency. However, the OLS estimations of the wage gap can be deceptive as generally both the worker and the establishment characteristics differ dramatically among sectors. We use benchmark OLS regressions and compare these estimates with Propensity Score Matching results. As the worker and job/firm characteristics become similar in both sectors, the public wage gap declines considerably, by about % 50, for men and for women.

JEL Codes: J31, J45

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1 Introduction

It is a widespread observation that there would be huge queues when government announces job openings in the public sector in Turkey. This observation is partially confirmed when there are public job openings for very low skilled workers and for some occupations such as school teachers. The lesser the qualifications required for the job the longer the queue would be.

Although the private sector provides the majority of job openings, the demand for public sector jobs at the low-to-mid level qualifications is generally higher. The highly qualified job seekers can pick either sector. There exist a steady flow of high skilled workers into and from the public to the private sector.

People may prefer public sector jobs to private sector for various reasons. Job security, fringe benefits or stable working hours can be some of these reasons Women can also demand public sector jobs for family reasons. The legal regulations are much more family friendly in the public sector.

The matching processes are rather different in public and private sectors. Public sector has to employ formal channels, i.e. formal job applications, interviews and even tests. Private sector on the other hand relies equally on informal channels, such as referral of existing workers and or of friends, relatives and acquaintances.

Public and private sector wage differentials play important roles in the allocation of skills as well as in unemployment dynamics such as unemployment duration, or unemployment rates in specific economic activities. For instance, if public sector jobs provide unobservable psychological benefits then unemployed job seekers may wait for longer periods even though certain private sector jobs are available.

Public sector is protected and does not need to set wages competitively. Political considerations can play decisive roles in the determination of public wages. Unions usually are stronger in the public sector. More importantly, the overall qualifications of the public sector workers are better their private sector companions.

The analysis of public wage gaps is important. We carry out such an analysis for Turkey by using Household Labor Force Survey. Our main contribution is to use matching models to estimate the public wage gaps for men and women separately. We find that the naive estimates of the public wage gaps through benchmark OLS regressions are not reliable. Once matching is introduced and similar workers are considered the wage gap declines by half, from % 30-35 to % 15-25 percent. Our second contribution is the wide range of our control variables. In addition to the variables used in the previous literature on Turkey, we control for both job characteristics and regions.

The remaining of the paper is organized as follows. Next section briefly reviews the related literature. The the third section discusses institutional setting in which wages are determined in Turkey. The fourth section introduces the data set and provides summary statistics. The empirical models and results are discussed in the fifth section. The last section concludes.

2 Related Studies

Generally it is expected to have public-private wage gaps. The empirical findings have pointed out public sector wage gaps in Europe and North America[4, 7]. The findings point to gaps within a range of 5-10 %.

There are a few studies that analyze the public private wage gap in developing economies. Panizza and Qiang (2005) [5] study the wage gap between the public and private sectors in 13 Latin American countries. They find that the public sector premium is above 10% for men in Brazil, Colombia, Costa Rica, Ecuador, and El Salvador. They observe that male public sector workers earn less than their private sector counterparts; for example 18 % in Bolivia, 17 % in Panama, nearly 8 % in Nicaragua and Peru. They also found bigger wage differences in favor of public workers for females (except Bolivia). The premium averages 7 % and ranges from 26 % in Colombia to a penalty of 21 % in Bolivia.

Papapetrou (2006) [6] estimated the public-private sector wage differential for 1997 in

Greece with quantile regression. He found that a significant part of the wage gap is due to workers endowment at all quantiles (at the median 51 % of wage differences). Especially at the upper quantiles, while the endowment effect becomes more important (at the 75th 80 % and at the 90th nearly 90 %), the unexplained part of the wage gap is declining.

A study by Tansel (2005) [14] finds that Results indicate that when controlled for observed characteristics and sample selection, for men, public administration wages are higher than private sector wages except at the university level where the wages are at par. State owned enterprise wages for men are higher than private sector wages. Similar results are obtained for women. Further, while wages of men and women are at parity in the public administration, there is a large gender wage-gap in the private sector in favor of men.

San and Polat (2012) [12] argue that after adjusting for correction using quantile regression, they find that the difference in the endowments between sectors at lower quantiles explains the majority of the raw wage gap; whereas a substantial amount of the raw wage gap is explained by the sector effect at higher quantiles. The mean wage gap due to the sector is more than 50 %.

Akhmenodjov and Izgi (2012) [1] estimate separate earnings functions for public and private sectors by gender with appropriate correction for selectivity bias. Their findings also suggest a considerable wage gap of more than 40%.

As we argue below that these finding are not robust. The main problem in the estimations are common to both OLS and quantile regressions which rely on the implicit assumption that workers are distributed randomly among public and private sectors.

3 Background on Industrial Relations and and Wage Setting in Turkey

Real wage developments followed a volatile pattern where there was a rapid decline right after the military coup in 1980 and temporary recovery in the first half of the 1990s. Partly due to the militant industrial action and partly due to the positive growth rates in the first half of 1990s, the real wages took a positive upturn. In public sector, the wages were doubled in 1991 and even though the private sector real wages rose as well, it was at a much lower pace. However the real wage increases came to a halt with the 1994 currency crisis and recovered only slightly until the beginning of 2000s. In 2001-2002, Turkey went through another round of banking and currency crisis and since then the real wages in both public and private sectors are declining with a more rapid pace in the latter. On the other hand the productivity gains have reached to %26 in the same period (Safak, 2006) [11]. One of the reasons for the divergent wage and productivity developments is the minimum wage legislation. Indeed, the main anchor for wage setting is the minimum wage in Turkey, which is decided by the state, and does not necessarily reflect the productivity trends. For instance, one third of people working in the private sector received wages less than or equal to the minimum wage in 2010.

Five different categories of workers are defined with regard to wage setting mechanisms in Turkey: namely, civil servants, employees of state-owned enterprises, employees covered by collective agreements in the private sector, formal private sector employees not covered by collective agreements, and informal sector employees. Substantial wage differentials are evident between these five categories, mainly due to the prevailing wage setting. In two of the five categories civil servants and employees of state owned enterprises (who make up about % 10 of manufacturing employment), where the government plays a key role in wage setting, and private sector employees covered by collective agreements (who account for around % 20 of employees in private manufacturing) wages are considerably higher compared with the other two categories.

4 Data and Descriptive Statistics

We use Household Labor Force Survey, 2010 carried out by Turkstat. The survey is comprehensive with more than 100 questions. First we constrain the sample by eliminating observations with no data on wages. Thus the employers, self-employed and the unpaid family workers as well as all the dependents and inactive persons are excluded. This step reduces the sample size from 449,289 to 86,321. Then we discard those who have reported zero or very small wages. Secondly, we take out the part-time and temporary workers. The remaining sample is still large compared to earlier samples used in other studies focusing on Turkey (Tansel 2005, San and Polat 2012, Akhmenodjov and zgi 2012). The pooled sample covering both men and female has a size of 76,590. The sample for the men is obviously larger, with 59,345 observations as compared to the sample for women with 17,245 observations.

The individual, firm and institutional covariates are considerably different for private sector male workers compared to public sector male workers. Public sector workers are older, more educated, more likely to be married and be migrant. They are almost all formal. The average tenure of public male workers is substantially greater than the private sector worker. They work in larger firms and they are more likely to hold an administrative position. The public workers are less likely to live and work in Istanbul compared to the private sector workers.

The striking difference among public and private sector female workers is in human capital. The share of university graduates in public sector is % 81 whereas it is only % 24 in the private sector. Moreover, for less educated (primary school or less) the ratios also differ dramatically, only % 2 in the public sector in contrast to %45 in the private sector. They are also older and their tenure is greater.

One third of the women in the private sector work in micro firms, firms with less than

Variables	Pri. Men	Pub. Men	Pri. Women	Pub. Women
Age 20-24	0.157	0.185	0.14	0.199
Age 25-29	0.118	0.186	0.101	0.169
Age 30-34	0.083	0.20	0.055	0.105
Age 34-39	0.038	0.117	0.023	0.035
Firm 1-9	0.390	0.095	0.33	0.061
Firm 10-24	0.121	0.098	0.135	0.123
Firm 25-49	0.171	0.226	0.194	0.256
Firm 50-99	0.208	0.334	0.227	0.312
Firm 100-249	0.050	0.092	0.051	0.09
Firm $250+$	0.061	0.155	0.062	0.157
Istanbul	0.194	0.053	0.246	0.088
Formal	0.764	0.975	0.764	0.999
HHsize	1.857	1.199	2.659	2.088
Migrant	0.380	0.485	0.389	0.653
Primary	0.615	0.227	0.448	0.025
High School	0.273	0.258	0.308	0.163
University	0.111	0.516	0.245	0.812
Married	0.714	0.893	0.464	0.707
Admin	0.066	0.184	0.056	0.09
Tenure	4.964	14.480	3.453	11.578
Network	0.138	0.006	0.16	0.008
Hours	56.14	43.05	51.40	39.42

 Table 1: Descriptive Summary Statistics

10 workers. This ratio is only % 6 in the public sector. Women in the public sector is more likely to have administrative positions (% 9) compared to the private sector (% 5.6). More than half of the public sector workers are migrants (% 65) and more likely to be married (% 70). These characteristics can be interrelated as it is common to move out of once city especially when the partner works on a different city.

Almost all the observable individual, firm and institutional variables favor the public sector workers, be them male or female. Thus it is expected that the public sector workers earn higher incomes.

5 Empirical Results

The aim is to figure out what would have been the wage gap if the workers in the public sector were employed in the private sector. However, the counterfactual observations are naturally unobtainable. The benchmark is simply treat public sector as a dummy variable and find the returns on being in the public sector. However, this method suffers from various deficiencies. First, the distribution is non-random. There is a selection bias. Second, there can be endogeneity issues as working in the public sector can be correlated with some unobservable characteristics (i.e. being diligent) that could affect wage earnings.

The general approach for dealing with the selection problem involves two steps. First step is to correct for the selection by first having a maximum likelihood regression and specifying Mills Ratios and then including these terms in OLS regressions specific for each sector. In the second step Oxaca-Blinder decomposition is used for to account for the differences in wage gaps between the two sectors due to the observable covariates. The same two step method can also be applied for the quantile regressions if one thinks that the relations between the wages and the observables are non-linear.

We use propensity score matching instead of following the general approach. Matching methods are more superior when selection variables are either hard to find or not fully exogenous. In the literature, household size, household income or health conditions are used as selection variables. We think that these or similar variables are not truly exogenous.

In matching, the treated and control groups are formed to make the likelihood of selection as similar as possible. In the next section, we carry out benchmark OLS regressions and matching estimations.

5.1 OLS Regressions

The benchmark method is straightforward linear estimation of the log monthly wage on various covariate variables and a dummy variable for working in the public sector. Our main interest is to have consistent and unbiased estimates for β in the following equation.

$$lnW = \alpha + \beta P + \gamma_i \sum X_i + \epsilon \tag{1}$$

We run three separate regressions. The first one is for the pooled sample. The second one is for the men and the third one is for the women. Given the substantial difference between the labor force participation rates of men and women in Turkey, the separate regressions are more meaningful.

We find that there appears a rather large wage gap, about % 30-35¹, between public and private sector workers, be them male or female. Our OLS results, though large are still smaller than the findings of San and Polat (2012) and Akhmenodjov and Izgi (2012). One reason for this difference lies in the fact that we have a higher number of covariates in the OLS regression than one finds in their studies. We control both worker and firm characteristics as well institutional and regional variables. The coefficients are similar in the pooled sample and in the separate samples for men and women.

The benchmark findings are likely to be overestimation of the wage gap as it considers as if the private sector and public sector workers are distributed randomly. However we

 $^{{}^{1}}e^{\beta}-1$ is used to get percentage differences.

	All	Men	Women
(Intercept)	6.25***	6.25^{***}	6.11***
	(0.01)	(0.01)	(0.03)
public	0.30^{***}	0.28^{***}	0.31^{***}
	(0.00)	(0.00)	(0.01)
female	-0.10^{***}		
	(0.00)		
married	0.07^{***}	0.09^{***}	0.04^{***}
	(0.00)	(0.01)	(0.01)
formal	0.27^{***}	0.23^{***}	0.26^{***}
	(0.00)	(0.00)	(0.01)
tenure	0.01^{***}	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)
HHsize	-0.04^{***}	-0.03^{***}	-0.04^{***}
	(0.00)	(0.00)	(0.00)
migrant	0.06^{***}	0.05^{***}	0.06^{***}
	(0.00)	(0.00)	(0.01)
regular	0.05^{***}	-0.02	0.15^{***}
	(0.01)	(0.01)	(0.02)
admin	0.22^{***}	0.22^{***}	0.27^{***}
	(0.00)	(0.01)	(0.01)
high	0.16^{***}	0.15^{***}	0.20^{***}
	(0.00)	(0.00)	(0.01)
univ	0.51^{***}	0.50^{***}	0.52^{***}
	(0.00)	(0.00)	(0.01)
Age 20-24	0.07^{***}	0.06^{***}	0.08^{***}
	(0.00)	(0.01)	(0.01)
Age 25-29	0.08***	0.08^{***}	0.08***
	(0.00)	(0.01)	(0.01)
Age 30-34	0.08***	0.08***	0.06***
	(0.01)	(0.01)	(0.01)
Age 35-39	0.07***	0.07^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)
Age 40-44	0.06***	$0.05^{}$	0.06^{+++}
T I 10.01	(0.01)	(0.01)	(0.02)
Firm 10-24	0.06***	0.10***	0.10***
T I AF (A	(0.00)	(0.01)	(0.01)
Firm 25-49	0.08	0.11	0.09
E: 50.00	(0.00)	(0.00)	(0.01)
Firm 50-99	0.08	0.14	0.12
E: 100.040	(0.00)	(0.00)	(0.01)
Firm 100-249	0.12	0.18	0.15
E: 050	(0.01)	(0.01)	(0.01)
F IFIN 250 +	(0.01)	0.24	(0.01)
Regional Dumriss	(U.U1) Included	(0.01) Included	(0.01) Included
D2	included	included	included
K-	0.61	0.60	0.67
Adj. R ²	0.61	0.60	0.67
Num. obs.	76590	59345	17245
p < 0.001, p	$< 0.01, \ "p <$	< 0.05	

Table 2: OLS Models

know from the descriptive summary statistics that the public sectors workers are much better qualified, more experiences and more likely to work in larger firms.

5.2 Matching

In order to deal with the selection issue at least partially and to decrease the bias due to endogeneity we use propensity score matching method. [2, 13] In our study, we have the treatment to be working in the Public sector, P = 1 indicates that the worker has received the treatment. Naturally, P = 0 means that the worker has not received the treatment, thus that worker is working in the private sector. The potential outcomes, the monthly wages, are then $W_{P=1}$ and $W_{P=0}$ respectively for the treated and the non-treated. It is impossible to estimate the individual treatment effect since there is no way to observe the potential outcome of a worker who has a treatment as if she had no treatment at the same time (the counterfactual case). However, ATT (Average Treatement Effect on the Treated) on those who received treatment compared to what they could have obtained without the treatment can be estimated, if some assumptions hold. The equation is as follows:

$$ATT = E(W_{P=1} - W_{P=0} \mid P = 1, X)$$
(2)

 $E(W_{P=1}|P=1,X)$ is observable from the observational data but $E(W_{P=0}|U=1,X)$ is unobservable and there is a missing counterfactual problem for the averages. Utilizing observed sample means to construct the counterfactual can lead to biases. Heckman et. al. (1998) divide the bias for ATT into three subcomponents:

$$E(W_{P=1}|P=1,X)(W_{P=0}|U=1,X) = B_1 + B_2 + B_3$$
(3)

where B_1 is the bias due to lack of sufficient overlap in the two groups (densities of common characteristics), B_2 is the bias due to differences in the distribution of observational characteristics X under the common support region and finally B_3 is the bias due to unobservables. This bias arises if the treatment is correlated with the unobserved characteristics. We have mentioned about this bias in discussing the endogeneity issue above.

The matching procedure tries to solve for the counterfactual problem by selecting a control group from the nontreated group such that the selected control group is as similar as possible to the treatment group based on observavle covariates. The Conditional Independence Assumption (CIA) is a necessary presumption which states that the outcome in the selected control group is independent of the treatment conditional on a set of covariates, X.

A potential difficulty with matching is the high dimensionability of characteristics. As the number of covariates increase the probability of matching the treatment group and the selected control group becomes very small. Rosenbaum and Rubin (1983) [8] propose to solve this dimensionability problem by using propensity score as a matching criteria.

$$p(X) = Pr(P = 1 \mid X) \forall X \in S$$
(4)

Treated and nontreated observations in the selected control group with the same (or very close) value of propensity scores have the same distribution of the observed covariates X and satisfy the balancing argument. Matching is a powerful technique in the sense that it can potentially minimize first two biases by avoiding the need to define a specific functional form for the outcome equation and by avoiding extrapolation beyond the common support.

We use nearest neighbor matching, Mahalanobis and caliper methods by using R package Matching (Sekhon 2011) [13].

The Table 3 is an illustration of how selection issue is severe and why we prefer to use propensity score matching. The variables used in the construction of propensity scores are listed in the probit regression are in the Appendix. The mean values of propensity scores for public sector workers, for both men and women, are in the order of more than 7 times higher than the private sector workers before matching.

For instance, mean propensity score for men declines from 0.7 to 0.499 after matching while the mean propensity score for the matched control group (the matched private sector workers) increases to 0.494 from 0.1.

 Table 3: Mean values of Propensity Scores Before and After Nearest Neighbor Matching

 Before Matching

 After Matching

	Treated	Control	Treated	Control
Men	0.7	0.1	0.499	0.494
Women	0.77	0.09	0.57	0.56

The resulting dataset is then used to estimate the wage gap. As the covariates that influence the likelihood of working in the public sector are similar in both the control and treatement groups in the new dataset, wage gap can be estimated as the coefficient on the union discrete variable.

In its simplest form, 1:1 nearest neighbor matching selects for each treated individual i the control individual j with the smallest distance from individual i. Although nearest or exact matching is in many ways the ideal (Imai et al., 2008) [3], the primary difficulty with the exact and Mahalanobis distance measures is that neither works very well when X is high dimensional. Requiring exact matches often leads to many individuals not being matched, which can result in larger bias than if the matches are inexact but more individuals remain in the analysis.

If the key covariates of interest are continuous, Mahalanobis matching within propensity score calipers (Rubin and Thomas, 2000)[10], defines the distance between individuals i and j. The goal is minimize this distance.

Rosenbaum and Rubin (1985)[9] discuss the choice of caliper size. When the variance of the linear propensity score in the treatment group is twice as large as that in the control group, a caliper of 0.2 standard deviations removes 98% of the bias in a normally distributed covariate. If the variance in the treatment group is much larger than that

Nearest N. ATT Estimate 0.14 0.14 0.15 Standard Errors 0.005 0.005 0.009 T-stat 18.04 16.87 16.79 Mahalonobis ATT Estimate 0.14 0.157 0.162 Standard Errors 0.004 0.008 0.008			All	Men	Women
Standard Errors 0.005 0.005 0.009 T-stat 18.04 16.87 16.79 Mahalonobis ATT Estimate 0.14 0.157 0.162 Standard Errors 0.004 0.008	Nearest N.	ATT Estimate	0.14	0.14	0.15
T-stat 18.04 16.87 16.79 Mahalonobis ATT Estimate 0.14 0.157 0.162 Standard Errors 0.004 0.008		Standard Errors	0.005	0.005	0.009
MahalonobisATT Estimate0.140.1570.162Standard Errors0.0040.008		T-stat	18.04	16.87	16.79
Standard Errors 0.004 0.008	Mahalonobis	ATT Estimate	0.14	0.157	0.162
		Standard Errors		0.004	0.008
T-stat 32.6 19.4		T-stat		32.6	19.4
Caliper (0.1) ATT Estimate 0.171 0.22	Caliper (0.1)	ATT Estimate		0.171	0.22
Standard Errors 0.06 0.01		Standard Errors		0.06	0.01
T-stat 32.7 19.5		T-stat		32.7	19.5
No obs. Treated 19938 14799 5139		No obs. Treated	19938	14799	5139
No obs. Matched 19938 14799 5139		No obs. Matched	19938	14799	5139
Total No obs. 76590 59345 17245		Total No obs.	76590	59345	17245

Table 4: Nearest Neighbor, Mahalonobis and Caliper Matching Models

in the control group, smaller calipers are necessary. Rosenbaum and Rubin (1985)[9] generally suggest a caliper of 0.25 standard deviations of the linear propensity score. We use a caliper of 0.1 in our matching exercise.

The results suggest that OLS estimations are largely off the mark overestimations. The wage gap declines from % 30-35 to % 15-25 depending on the gender and matching method.

In order to check the balance on selected covariates achieved by matching, we illustrate the following table. Matching balance results confirm our findings. We include the table for men but similar results are obtained for women.

The "Propensity Score" variable is the fitted values of the probit estimation results (see Appendix). The improvement in the balance of propensity scores is visible. There is almost a perfect balance for other covariates, except for "tenure". However the importance of tenure is the least significant in the determination of wages when other covariates are controlled for.

Variables	Before Matching		T-test	After Matching		T-test
	Public	Private		Public	Private	
University	0.516	0.11	2.22e-16	0.516	0.516	1
High School	0.257	0.273	0.0001	0.257	0.257	1
Firm 100-249	0.092	0.049	2.22e-16	0.092	0.092	1
Firm $250 +$	0.154	0.06	2.22e-16	0.154	0.154	1
Formal	0.974	0.764	2.22e-16	0.974	0.974	1
Admin	0.183	0.065	2.22e-16	0.183	0.183	1
Tenure	14.48	4.964	2.22e-16	14.48	14.296	2.22e-16

Table 5: Matching Balance for Men

6 Conclusion

The public sector wage is higher than the private sector wage in Turkey. However, the pay gap turns out to be dramatically lower if an appropriate method is chosen. We have used the most extensive data set on the issue and employed propensity score matching methods to study the real wage gap for men and women working in public and private sectors. We have found that the estimated real wage gaps are in the order of 15-20%. The previous studies overestimate the wage gaps as they do not take the sample selection and endogeneity issues properly.

Our finding may relate to the fact that in the recent decades there has been a considerable pressure on public expenditures. Future studies should also focus on non-material benefits of public sector jobs. Job security, limited working hours with overpay, and welfare benefits such as access to childcare facilities are also important for sector choice.

7 Appendix

	Men	Women
(Intercept)	-1.42^{***}	-1.92^{***}
	(0.15)	(0.54)
formal	1.20^{***}	3.64^{***}
	(0.07)	(0.47)
married	-0.27^{***}	0.15^{*}
	(0.06)	(0.06)
tenure	0.12^{***}	0.16^{***}
	(0.00)	(0.01)
HHsize	-0.22^{***}	-0.20^{***}
	(0.02)	(0.04)
network	-1.35^{***}	-1.29^{***}
	(0.11)	(0.18)
migrant	0.57***	0.85***
	(0.03)	(0, 06)
hours	-0.11***	-0.17***
	(0.00)	(0.01)
admin	-0.17***	_0.03***
admin	(0.05)	-0.33
high	0.57***	1 40***
mgn	(0.04)	(0.12)
	(0.04)	(0.12)
univ	1.99	2.00
	(0.04)	(0.11)
Age 20-24	0.10	-0.06
1 05 00	(0.05)	(0.08)
Age 25-29	0.44	-0.18
	(0.06)	(0.10)
Age 30-34	0.52***	-0.13
	(0.06)	(0.12)
Age 35-39	0.77***	-0.10
	(0.07)	(0.15)
Age 40-44	0.97^{***}	-0.93^{***}
	(0.08)	(0.22)
Firm 10-24	0.70^{***}	0.74^{***}
	(0.06)	(0.12)
Firm 25-49	1.02***	1.06^{***}
	(0.05)	(0.11)
Firm 50-99	1.13^{***}	1.10^{***}
	(0.05)	(0.10)
Firm 100-249	1.16^{***}	1.51^{***}
	(0.07)	(0.13)
Firm $250 +$	1.44^{***}	1.78^{***}
	(0.06)	(0.12)
AIC	29677.45	7942.66
BIC	30118.02	8322.67
Log Likelihood	-14789.73	-3922.33
Deviance	29579.45	7844.66
NT 1	59345	17245
Num. obs.	00010	

Table 6: Probit Regression for Propensity Score Matching

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