# Work-Life Program Participation and Employee Work Attitudes: A Quasi-Experimental Analysis Using Matching Strategies

Sun Young Kim
University of Georgia

David Lee
University of Hawaii

# Work & Life Balance

**'워라밸' 지키는 공무원 증가 추세**
한겨레 - Mar 19, 2018
인사처가 2017년 국가**공무원**의 유연근무제 이용 현황을 확인해보니 지난해 각 부처의 유연근무제 이용자는 모두 11만6131명으로 전년인 2016 ...

**지난해 유연근무제 이용 공무원 3배 늘었다**
디지털타임스 - Mar 20, 2018
인사혁신처는 **지난해** 국가**공무원**의 **유연근무제 이용**현황을 조사한 결과 각 부처에서 **유연근무제**를 이용한 **공무원**이 전년보다 2**배** 이상 증가했다고 ...

**공무원 '근무혁신'...주 3.5일 근무 가능해진다**
대한민국정책포털 korea.kr - Feb 21, 2016
앞으로 **공무원**들이 **근무**시간을 자율적으로 잘 설계하면 **주 3.5일 근무**도 **가능**해질 전망이다. 또 부서별로 월간 초과**근무** 총량을 미리 정해 불필요한 ...

**"야근 NO" 삶의 질에 눈뜬 공직사회...지자체 '워라밸' 붐**
연합뉴스 - Apr 3, 2018
이병훈 중앙대학교 사회학과 교수는 "우리나라가 선진국 수준**의** 근로 여건을 갖추기 위해 **공직사회**부터 선도적으로 **워라밸** 문화를 장려해야 민간 ...

**공무원, 임신 기간 내내 단축근무...육아시간도 확대**
매일경제 - Feb 20, 2018
그 대책의 하나로 초과근무**시간** 저축연가제를 도입해 초과근무를 하면 상대적으로 덜 바쁠 때 그만큼 **단축근무** 또는 연가로 활용할 수 있도록 '**시간** ...

# Work-Life Programs

- The primary purpose of work-life programs (WLPs) is to create a supportive work environment for employees by providing them with greater choices and flexibility in coordinating work and personal lives.
- While also commonly known as family-friendly policies, WLPs do not target any one particular group of employees facing family-related issues but include a broad set of benefits and policies offered to a wide range of employees.
- Many public organizations have begun to institute various policies and programs to enhance work-life balance.

# WLP Literature

- The effects of WLPs on job satisfaction, job involvement, organizational commitment, work motivation, turnover intention, turnover rates, and organizational performance have been extensively studied in previous research.

- However, previous studies have produced somewhat mixed results.
  - Empirical studies investigating whether WLPs can be categorized into different types and whether they have varying impacts on work outcomes are relatively scarce.
  - Nonrandom treatment assignment (i.e., program participation) in observational studies may generate selection bias in the estimation of the program impact.

# Research Question

- Does participating in distinct types of WLPs have varying impacts on employee work attitudes?

**WLP Participation**
- Work-oriented
- Life-oriented

→

**Employee Satisfaction & Commitment**

# WLP Typology

- Typology of Workplace Policies (Hoyman & Duer, 2004)

| | |
|---|---|
| *1) Family/Personal*<br>Pregnancy leaves<br>Maternity/Paternity leaves<br>Personal leave<br>Family medical<br>Child care: on-site and vouchers to subsidize<br>Paid vacation<br>Bereavement leaves<br>Flexible use of sick days<br>Flex plans and cafeteria plans<br>Health care benefits | *2) Removing Impediments to Work*<br>Employee assistance programs<br>Homework<br>Telecommuting<br>Flexplace<br>Flextime |
| *3) Training & Education*<br>Skill acquisition<br>Personal development<br>Higher education | *4) Nontraditional Incentives*<br>Company car<br>Parking prizes: Employee of the month<br>Presenteeism creative incentive programs<br>Conversion of sick pay to cash<br>Recognition awards<br>Gyms<br>Stress management<br>On-site oil change and lubrication jobs |

# WLP Typology

- WLPs can be categorized into two different types, and each type of program has a distinct goal, focus, and target group.

| Type of WLP | Goal | Focus | Target Audience |
|---|---|---|---|
| Work-oriented programs | Providing flexibility in work location and time to help complete job duties efficiently | Both worker and organization | Universal |
| Life-oriented programs | Providing support for family responsibilities and personal issues | Worker | Families |

# Social Exchange Theory

- When employees receive favorable treatments from their organization, they feel obligated to reciprocate by making additional efforts and acting more favorably toward the organization (Blau, 1964; Gouldner, 1960).
- Individuals who participate in WLPs would react positively to such benefits and become willing to repay the organization with improved satisfaction and commitment.
- However, different types of WLPs may generate dissimilar levels of social exchanges between employee and organization.

# Social Exchange Theory

- For organizations, the advantages of work-oriented programs can be direct and immediate, realized by employees performing tasks more efficiently and effectively, while the advantages of life-oriented programs are rather indirect and often require a certain period of time to be realized.

- Life-oriented programs "may be viewed as an act of goodwill rather than a way to get employees to work harder, which in turn may make employees feel more obligated to reciprocate by demonstrating loyalty to the organizations" (Caillier, 2013, p. 359).

- Employees who receive life-oriented benefits would have stronger obligations to return the investment.

# Hypotheses

- Hypothesis 1. Participation in work-oriented programs (telework and alternative work schedules) would not lead to an increase in employees' (a) job satisfaction, (b) organizational satisfaction, and (c) affective commitment.

- Hypothesis 2. Participation in life-oriented programs (child care and elder care) would lead to an increase in employees' (a) job satisfaction, (b) organizational satisfaction, and (c) affective commitment.

# Matching Methods

- The voluntary nature of program participation introduces the potential for selection bias.
- Participants may differ from nonparticipants in many ways besides the effect of the program, so the simple difference in outcomes between participants and nonparticipants will not necessarily identify the impact of the program.
- The effectiveness of programs can be evaluated through rigorous nonexperimental evaluation methods, such as matching.

# Selection Bias

| | Telework | | Alternative Work Schedules | |
|---|---|---|---|---|
| | Participated | Not Participated | Participated | Not Participated |
| Work Location (1 = field) | 0.493 | 0.624 | 0.554 | 0.591 |
| Supervisory Level | 1.351 | 1.403 | 1.328 | 1.421 |
| Gender (1 = female) | 0.526 | 0.429 | 0.494 | 0.445 |
| Minority Status (1 = minority) | 0.316 | 0.341 | 0.337 | 0.329 |
| Age Group | 3.299 | 3.368 | 3.360 | 3.332 |
| Pay Category | 3.756 | 3.356 | 3.514 | 3.492 |
| Federal Tenure | 4.170 | 4.040 | 4.188 | 4.022 |
| Agency Tenure | 3.284 | 3.235 | 3.301 | 3.222 |
| Supervisory Support | 4.227 | 3.949 | 4.113 | 4.009 |

| | Child Care Programs | | Elder Care Programs | |
|---|---|---|---|---|
| | Participated | Not Participated | Participated | Not Participated |
| Work Location (1= field) | 0.520 | 0.578 | 0.534 | 0.577 |
| Supervisory Level | 1.352 | 1.385 | 1.357 | 1.385 |
| Gender (1 = female) | 0.550 | 0.462 | 0.583 | 0.462 |
| Minority Status (1 = minority) | 0.453 | 0.329 | 0.504 | 0.329 |
| Age Group | 3.040 | 3.351 | 3.680 | 3.337 |
| Pay Category | 3.393 | 3.504 | 3.368 | 3.503 |
| Federal Tenure | 3.900 | 4.092 | 4.581 | 4.078 |
| Agency Tenure | 3.108 | 3.257 | 3.527 | 3.248 |
| Supervisory Support | 4.127 | 4.048 | 4.161 | 4.048 |

# Why Use Matching?

In matching, we compare apples with apples and oranges with oranges!

- Matching: Any method that aims to equate (or "balance") the distribution of covariates in the treated and control groups (Stuart, 2010)
- The goal of matching is to reduce bias due to observed differences in the estimation of the treatment effect.
  - Choose well-matched samples of the original treated and control groups and compare how outcomes differ for participants relative to *observationally similar* nonparticipants.
- Matching replicates a randomized experiment as closely as possible by obtaining treated and control groups with similar covariate distributions.

# Applications of Matching in Program Evaluation

- Labor market and training programs
- Antipoverty welfare programs
- Health insurance
- Research and development subsidies and patent laws
- Teachers' performance incentives
- Electoral reform

# When to Use Matching: Assumptions

- Two conditions must be satisfied to implement matching (Heinrich et al., 2010).
- Conditional Independence Assumption (CIA)
  - Selection into treatment is based only on observable characteristics of the eligible units, and after conditioning on these variables influencing participation, the potential outcomes in the absence of treatment are independent of treatment status.
- Common Support (or Overlap) Condition
  - There is sufficient overlap in the characteristics of the treated and untreated units to find adequate matches so that each treatment unit can be matched with an untreated unit.

# Matching vs. Regression

- One of the advantages of matching over regression is that matching explicitly clarifies the region of common support.
  - Regression incorporates data from unmatched cases; thus, participants who do not have common support across all covariates are included in the estimate.
  - It can increase bias when there are large differences in the means and variances of the covariates in the treated and control groups.
  - Regression models perform poorly in situations where there is insufficient overlap (Stuart, 2010).
  - Standard regression diagnostics will not warn researchers when there is insufficient overlap to reliably estimate causal effects.

# Steps in Implementing Matching Methods

- Step 1: Define "closeness"
- Step 2: Implement a matching method
- Step 3: Diagnose the quality of matching
- Step 4: Estimate the treatment effect

# Step 1: Define Closeness

- Determine the measure of distance (or similarity) between two individuals.

- Mahalanobis distance matching (MDM)

$$D_{ij} = \left(X_i - X_j\right)^T \Sigma^{-1} (X_i - X_j)$$

$X$: a vector of matching covariates
$\Sigma$: variance covariance matrix of $X$

- Propensity score matching (PSM)
  - The probability of receiving the treatment given a set of observed covariates

$$p_k = \Pr(T_k = 1|X)$$

$T$: treatment status
$X$: a vector of matching covariates

  - The distance between treated and untreated units is calculated as the absolute difference between propensity scores.

$$D_{ij} = \left|p_i - p_j\right|$$

# Step 1: Define Closeness (Cont'd)

- Determine which covariates to include in the matching process.
- If the matching process is to successfully mitigate potential bias, it has to be done considering a full range of covariates across which the treatment and comparison units might differ.
- Covariates must be measured at some period of time before the treatment, and the variables that may have been affected by the treatment of interest should not be included in the matching process.

# Step 2: Implement a Matching Method

- Nearest neighbor matching
  - $k$:1 nearest neighbor matching selects $k$ control individuals with the smallest distance for each treated individual.
- Number of neighbors ($k$): the number of comparison units matched to each treatment unit
  - Selecting multiple controls for each treated individual will generally increase bias, since the 2nd, 3rd, and 4th closest matches are further away from the treated individual than is the 1st closest match.
- Matching with or without replacement: whether or not controls can be used as matches for more than one treated individual
  - Matching with replacement can often decrease bias because controls that look similar to many related individuals can be used multiple times.
  - It is more common to use matching with replacement.

# Step 2: Implement a Matching Method (Cont'd)

- Caliper matching
  - To avoid the risk of poor matches, specify a "caliper" or maximum distance by which a match can be made.
  - It includes in the comparison only those cases that are sufficiently "close" to a given treated case, which are available in the caliper.
  - It does not limit the number of cases that are matched with a given participant.
  - Estimates are more stable (and make better use of available data) if they consider all comparison cases that are sufficiently close to a given treated case.

# Step 2: Implement a Matching Method (Cont'd)

- Assessing common support
  - While we assume that there is substantial overlap between treated and control groups, there may not be complete overlap in some situations.
  - For example, many of the control individuals may be very different from all of the treatment group members, making them inappropriate as points of comparison when estimating the impact of a program.
  - Discard individuals that are outside the region of common support.

# Step 3: Diagnose the Quality of Matching

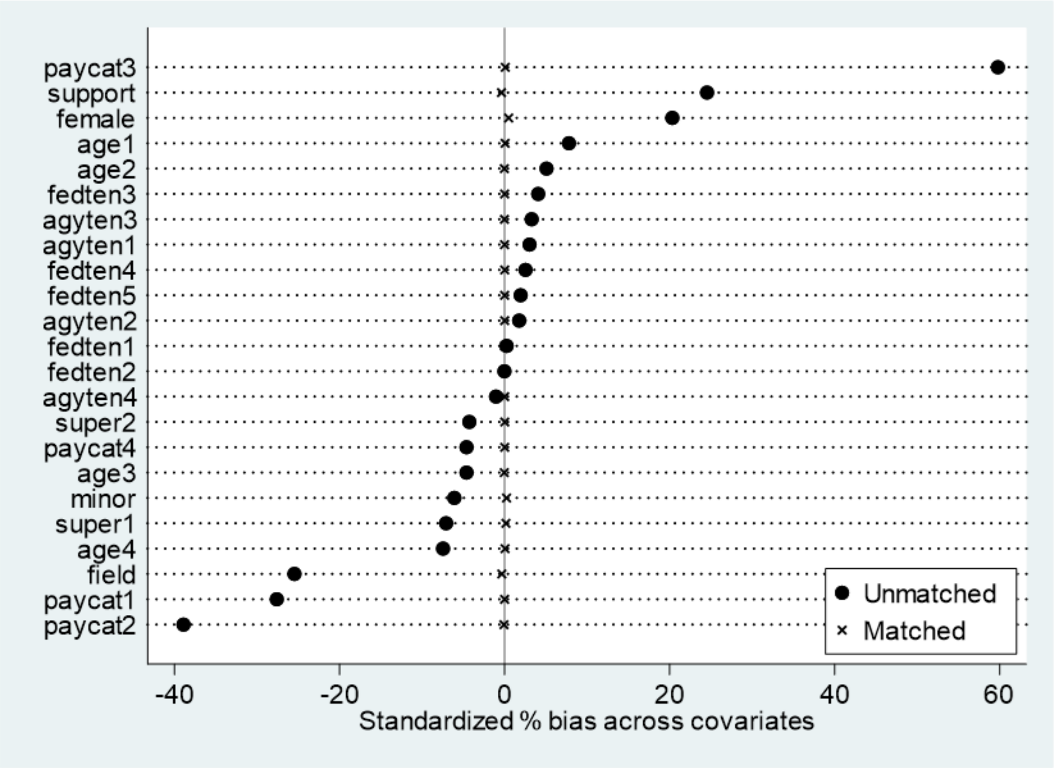
- Examine the balance of covariates resulting from the matching method.
- A matching method that results in highly imbalanced samples should be rejected, and alternative methods should be attempted until a well-balanced sample is attained.

# Step 3: Diagnose the Quality of Matching (Cont'd)

- t-tests of differences between covariate means of the treatment and comparison units before and after matching
- Standardized bias (or standardized difference in means)
  - The difference in means of each covariate, divided by the standard deviation in the full treated group
- Graphical diagnostics

```
pstest field super1 super2 female minor age1 age2 age3 age4 paycat1 paycat2 paycat3
paycat4 fedten1 fedten2 fedten3 fedten4 fedten5 agyten1 agyten2 agyten3 agyten4
support, both graph

-----------------------------------------------------------------------------------
                Unmatched |       Mean               %reduct |     t-test    |  V(T)/
Variable          Matched | Treated Control    %bias  |bias| |    t    p>|t| |  V(C)
--------------------------+----------------------------------+---------------+----------
field                   U | .46541   .59152    -25.5         | -49.03  0.000 |      .
                        M | .46541   .46709     -0.3    98.7 |  -0.59  0.553 |      .
                          |                                  |               |
super1                  U | .14939   .17552     -7.1         | -13.54  0.000 |      .
                        M | .14939   .14883      0.2    97.8 |   0.28  0.780 |      .
                          |                                  |               |
super2                  U | .09868   .11178     -4.3         |  -8.17  0.000 |      .
                        M | .09868   .09863      0.0    99.6 |   0.03  0.977 |      .
                          |                                  |               |
female                  U | .51678   .41588     20.3         |  39.14  0.000 |      .
                        M | .51678   .51432      0.5    97.6 |   0.86  0.387 |      .
                          |                                  |               |
minor                   U | .31524   .34383     -6.1         | -11.67  0.000 |      .
                        M | .31524   .31414      0.2    96.2 |   0.42  0.677 |      .
                          |                                  |               |
age1                    U | .16445   .13658      7.8         |  15.11  0.000 |      .
                        M | .16445   .16424      0.1    99.2 |   0.10  0.921 |      .
                          |                                  |               |
age2                    U | .30294   .27985      5.1         |   9.79  0.000 |      .
                        M | .30294   .30309     -0.0    99.4 |  -0.06  0.956 |      .
                          |                                  |               |
age3                    U |  .3554   .37765     -4.6         |  -8.86  0.000 |      .
                        M |  .3554   .35563     -0.0    99.0 |  -0.08  0.934 |      .
                          |                                  |               |
age4                    U | .12134   .14673     -7.5         | -14.22  0.000 |      .
                        M | .12134   .12118      0.0    99.4 |   0.09  0.931 |      .
                          |                                  |               |
paycat1                 U |  .0103   .06103    -27.6         | -49.79  0.000 |      .
                        M |  .0103    .0103      0.0   100.0 |   0.00  1.000 |      .
                          |                                  |               |
paycat2                 U | .26261   .44527    -38.9         | -73.94  0.000 |      .
                        M | .26261     .263     -0.1    99.8 |  -0.16  0.877 |      .
                          |                                  |               |
paycat3                 U | .65458   .36825     59.8         | 114.77  0.000 |      .
                        M | .65458   .65422      0.1    99.9 |   0.13  0.895 |      .
                          |                                  |               |
paycat4                 U | .06676   .07875     -4.6         |  -8.81  0.000 |      .
                        M | .06676   .06673      0.0    99.7 |   0.02  0.982 |      .
                          |                                  |               |
fedten1                 U | .07949   .07882      0.3         |   0.48  0.630 |      .
                        M | .07949   .07949      0.0   100.0 |   0.00  1.000 |      .
```


paycat3
support
female
age1
age2
fedten3
agyten3
agyten1
fedten4
fedten5
agyten2
fedten1
fedten2
agyten4
super2
paycat4
age3
minor
super1
age4
field
paycat1
paycat2
Unmatched
Matched
-40
-20
0
20
40
60
Standardized % bias across covariates

# Step 4: Estimate the Treatment Effect

- Once each treated unit has been matched with one or more untreated units, the impact of the program is estimated as a weighted average of the difference in outcomes between treated and untreated.

# Selection on Unobservables

- A critique of any nonexperimental study is that there may be *unobserved* variables related to both treatment assignment and the outcome, violating the conditional independence assumption and biasing the treatment effect estimates.
- Unfortunately, the CIA assumption is not directly testable.
- Analyses can be done to assess sensitivity of the results to the existence of an unobserved confounder related to both treatment assignment and the outcome.

# Selection on Unobservables (Cont'd)

- Sensitivity analysis using Rosenbaum's bound (Rosenbaum, 2002)
  - Bounds can be created for the treatment effects, given a range of potential correlations of a hypothetical unobserved covariate with treatment assignment and the outcome.

- Difference-in-differences matching (Heinrich et al., 2010)
  - If pretreatment data are available, and under the assumption that unobserved variables are time-invariant (that is, there value does not change with time), the effect can be cancelled out by taking the difference in outcomes before and after the program.
  - Outcome is measured in changes between pre- and post-treatment periods instead of in levels.

# Data

- Federal Employee Viewpoint Survey (U.S. Office of Personnel Management, 2011)
  - The survey has been conducted by the OPM since 2002 to examine employees' perceptions of and attitudes toward the federal workplace.
  - Among 417,128 federal government employees, 266,376 employees completed the survey, resulting in a response rate of 64%.
  - After removing the observations that had missing data on one or more variables, the final sample size was 153,702.

# Treatment Variables

- Treatment status: whether or not the respondent participated in a particular WLP
- "Do you participate in the following Work/Life programs?" (1 = participation; 0 = nonparticipation).
  - Telework
  - Alternative work schedules
  - Child care programs
  - Elder care programs

# Treatment Variables

- Telework frequency
  - 3 or more days per week
  - 1 or 2 days per week
  - 1 or 2 days per month
  - At least on a short-term basis

# Outcome Variables

- Job satisfaction
  - "Considering everything, how satisfied are you with your job?"
- Organizational satisfaction
  - "Considering everything, how satisfied are you with your organization?"
- Affective commitment (Cronbach's alpha = 0.792)
  - "My work gives me a feeling of personal accomplishment."
  - "I like the kind of work I do."
  - "I recommend my organization as a good place to work."
- All outcome variables were standardized before analysis.

# Matching Covariates

- Gender, minority status, age group, supervisory level, work location, pay category, federal and agency tenure, and supervisory support for work-life balance

- Dummy variables were created for categorical variables.

# Matching in Stata: psmatch2

- Mahalanobis distance matching (1:1 nearest neighbor with replacement)

```
ssc install psmatch2, replace

psmatch2 telework, mahalanobis(field super1 super2 female minor age1 age2 age3 age4 paycat1
paycat2 paycat3 paycat4 fedten1 fedten2 fedten3 fedten4 fedten5 agyten1 agyten2 agyten3
agyten4 support) outcome(stdjobsat stdorgsat stdacomm) ai(2)
----------------------------------------------------------------------------------------
        Variable     Sample |    Treated     Controls   Difference         S.E.   T-stat
----------------------------+-----------------------------------------------------------
       stdjobsat  Unmatched | .116272977    .06006269   .056210287   .004993855    11.26
                        ATT | .116272977   .139242683  -.022969706   .024452246    -0.94
----------------------------+-----------------------------------------------------------
       stdorgsat  Unmatched |  .13019068   .068743379   .061447301   .005003151    12.28
                        ATT |  .13019068   .164033005  -.033842325    .02402043    -1.41
----------------------------+-----------------------------------------------------------
        stdacomm  Unmatched | .118352755    .05155455   .066798205   .005021833    13.30
                        ATT | .118352755   .121889474  -.003536719   .029188595    -0.12
----------------------------+-----------------------------------------------------------
Note: Sample S.E.

            | psmatch2:
 psmatch2:  |   Common
 Treatment  |  support
assignment  | On suppor |     Total
------------+-----------+----------
 Untreated  |    91,885 |    91,885
   Treated  |    61,817 |    61,817
------------+-----------+----------
     Total  |   153,702 |   153,702
```

```
pstest field super1 super2 female minor age1 age2 age3 age4 paycat1 paycat2 paycat3
paycat4 fedten1 fedten2 fedten3 fedten4 fedten5 agyten1 agyten2 agyten3 agyten4
support, both graph
```

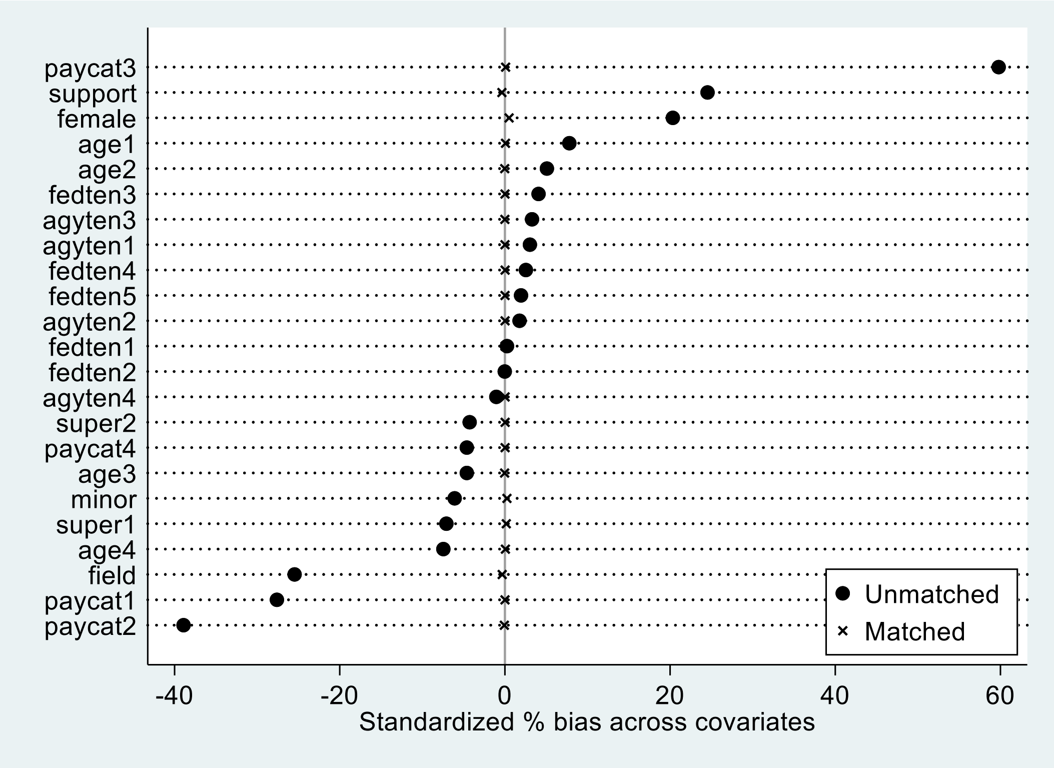
| Variable | Unmatched Matched | Mean Treated | Mean Control | %bias | %reduct \|bias\| | t-test t | t-test p>\|t\| | V(T)/ V(C) |
|---|---|---|---|---|---|---|---|---|
| field | U | .46541 | .59152 | -25.5 | | -49.03 | 0.000 | . |
| | M | .46541 | .46709 | -0.3 | 98.7 | -0.59 | 0.553 | . |
| super1 | U | .14939 | .17552 | -7.1 | | -13.54 | 0.000 | . |
| | M | .14939 | .14883 | 0.2 | 97.8 | 0.28 | 0.780 | . |
| super2 | U | .09868 | .11178 | -4.3 | | -8.17 | 0.000 | . |
| | M | .09868 | .09863 | 0.0 | 99.6 | 0.03 | 0.977 | . |
| female | U | .51678 | .41588 | 20.3 | | 39.14 | 0.000 | . |
| | M | .51678 | .51432 | 0.5 | 97.6 | 0.86 | 0.387 | . |
| minor | U | .31524 | .34383 | -6.1 | | -11.67 | 0.000 | . |
| | M | .31524 | .31414 | 0.2 | 96.2 | 0.42 | 0.677 | . |
| age1 | U | .16445 | .13658 | 7.8 | | 15.11 | 0.000 | . |
| | M | .16445 | .16424 | 0.1 | 99.2 | 0.10 | 0.921 | . |
| age2 | U | .30294 | .27985 | 5.1 | | 9.79 | 0.000 | . |
| | M | .30294 | .30309 | -0.0 | 99.4 | -0.06 | 0.956 | . |
| age3 | U | .3554 | .37765 | -4.6 | | -8.86 | 0.000 | . |
| | M | .3554 | .35563 | -0.0 | 99.0 | -0.08 | 0.934 | . |
| age4 | U | .12134 | .14673 | -7.5 | | -14.22 | 0.000 | . |
| | M | .12134 | .12118 | 0.0 | 99.4 | 0.09 | 0.931 | . |
| paycat1 | U | .0103 | .06103 | -27.6 | | -49.79 | 0.000 | . |
| | M | .0103 | .0103 | 0.0 | 100.0 | 0.00 | 1.000 | . |
| paycat2 | U | .26261 | .44527 | -38.9 | | -73.94 | 0.000 | . |
| | M | .26261 | .263 | -0.1 | 99.8 | -0.16 | 0.877 | . |
| paycat3 | U | .65458 | .36825 | 59.8 | | 114.77 | 0.000 | . |
| | M | .65458 | .65422 | 0.1 | 99.9 | 0.13 | 0.895 | . |
| paycat4 | U | .06676 | .07875 | -4.6 | | -8.81 | 0.000 | . |
| | M | .06676 | .06673 | 0.0 | 99.7 | 0.02 | 0.982 | . |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| fedten1 | U | .07949 | .07882 | 0.3 | | 0.48 | 0.630 | . |
| | M | .07949 | .07949 | 0.0 | 100.0 | 0.00 | 1.000 | . |
| fedten2 | U | .16516 | .16524 | -0.0 | | -0.04 | 0.969 | . |
| | M | .16516 | .1652 | -0.0 | 56.4 | -0.02 | 0.988 | . |
| fedten3 | U | .105 | .09286 | 4.1 | | 7.87 | 0.000 | . |
| | M | .105 | .105 | 0.0 | 100.0 | -0.00 | 1.000 | . |
| fedten4 | U | .11188 | .104 | 2.5 | | 4.90 | 0.000 | . |
| | M | .11188 | .11185 | 0.0 | 99.6 | 0.02 | 0.986 | . |
| fedten5 | U | .40052 | .39099 | 1.9 | | 3.75 | 0.000 | . |
| | M | .40052 | .4005 | 0.0 | 99.8 | 0.01 | 0.995 | . |
| agyten1 | U | .10499 | .09589 | 3.0 | | 5.84 | 0.000 | . |
| | M | .10499 | .10499 | 0.0 | 100.0 | -0.00 | 1.000 | . |
| agyten2 | U | .1905 | .1836 | 1.8 | | 3.41 | 0.001 | . |
| | M | .1905 | .19047 | 0.0 | 99.5 | 0.01 | 0.988 | . |
| agyten3 | U | .22154 | .20808 | 3.3 | | 6.32 | 0.000 | . |
| | M | .22154 | .22161 | -0.0 | 99.5 | -0.03 | 0.978 | . |
| agyten4 | U | .2862 | .29092 | -1.0 | | -2.00 | 0.045 | . |
| | M | .2862 | .28615 | 0.0 | 99.0 | 0.02 | 0.985 | . |
| Support | U | 4.2695 | 4.0416 | 24.5 | | 46.66 | 0.000 | 0.80* |
| | M | 4.2695 | 4.274 | -0.5 | 98.0 | -0.92 | 0.357 | 1.04* |

* if variance ratio outside [0.98; 1.02] for U and [0.98; 1.02] for M

| Sample | Ps R2 | LR chi2 | p>chi2 | MeanBias | MedBias | B | R | %Var |
|---|---|---|---|---|---|---|---|---|
| Unmatched | 0.110 | 22697.00 | 0.000 | 11.4 | 4.6 | 81.7* | 0.74 | 100 |
| Matched | 0.000 | 2.13 | 1.000 | 0.1 | 0.0 | 0.8 | 1.02 | 100 |

* if B>25%, R outside [0.5; 2]


paycat3
support
female
age1
age2
fedten3
agyten3
agyten1
fedten4
fedten5
agyten2
fedten1
fedten2
agyten4
super2
paycat4
age3
minor
super1
age4
field
paycat1
paycat2
-40
-20
0
20
40
60
Standardized % bias across covariates
Unmatched
Matched

# Descriptive Statistics

| Variable | Mean | Min | Max |
|---|---|---|---|
| Telework | 0.40 | 0 | 1 |
| Alternative Work Schedules | 0.43 | 0 | 1 |
| Child Care Programs | 0.03 | 0 | 1 |
| Elder Care Programs | 0.02 | 0 | 1 |
| Job Satisfaction | 3.89 | 1 | 5 |
| Organizational Satisfaction | 3.73 | 1 | 5 |
| Affective Commitment | 4.04 | 1 | 5 |
| Supervisory Support | 4.13 | 1 | 5 |
| Gender (1 = Female; 0 = Male) | 0.46 | 0 | 1 |
| Minority Status (1 = Minority; 0 = Non-Minority) | 0.33 | 0 | 1 |
| Age Group | | | |
| 29 and Under | 0.06 | 0 | 1 |
| 30-39 | 0.15 | 0 | 1 |
| 40-49 | 0.29 | 0 | 1 |
| 50-59 | 0.37 | 0 | 1 |
| 60 or Older | 0.13 | 0 | 1 |
| Supervisory Level | | | |
| Non-Supervisors and Team Leaders | 0.72 | 0 | 1 |
| Supervisors | 0.17 | 0 | 1 |
| Managers and Executives | 0.11 | 0 | 1 |
| Work Location (1 = Field; 0 = Headquarters) | 0.54 | 0 | 1 |
| Pay Category | | | |
| Federal Wage System | 0.03 | 0 | 1 |
| GS 1-6 | 0.04 | 0 | 1 |
| GS 7-12 | 0.37 | 0 | 1 |
| GS 13-15 | 0.48 | 0 | 1 |
| SES/SL/ST/Other | 0.08 | 0 | 1 |
| Federal Tenure | | | |
| Up to 3 Years | 0.15 | 0 | 1 |
| 4-5 Years | 0.08 | 0 | 1 |
| 6-10 Years | 0.16 | 0 | 1 |
| 11-14 Years | 0.10 | 0 | 1 |
| 15-20 Years | 0.11 | 0 | 1 |
| More Than 20 Years | 0.39 | 0 | 1 |
| Agency Tenure | | | |
| Up to 3 Years | 0.21 | 0 | 1 |
| 4-5 Years | 0.10 | 0 | 1 |
| 6-10 Years | 0.19 | 0 | 1 |
| 11-20 Years | 0.21 | 0 | 1 |
| More Than 20 Years | 0.29 | 0 | 1 |

# Treatment and Control Groups

| | Participated | Not Participated |
|---|---|---|
| Telework | 61,817 | 91,885 |
| Alternative Work Schedules | 66,159 | 87,543 |
| Child Care Programs | 4,277 | 149,425 |
| Elder Care Programs | 3,152 | 150,550 |

(N = 156,620)

# Estimation of Treatment Effect

- When interpreting the results, it is important to evaluate the robustness of the estimations by changing the matching algorithms or by altering the parameters of a given algorithm.

- Regression with covariates
- MDM nearest neighbor matching (1:1 with replacement)
- PSM nearest neighbor matching (1:1 with replacement)
- PSM nearest neighbor matching (1:1 without replacement)
- PSM caliper matching

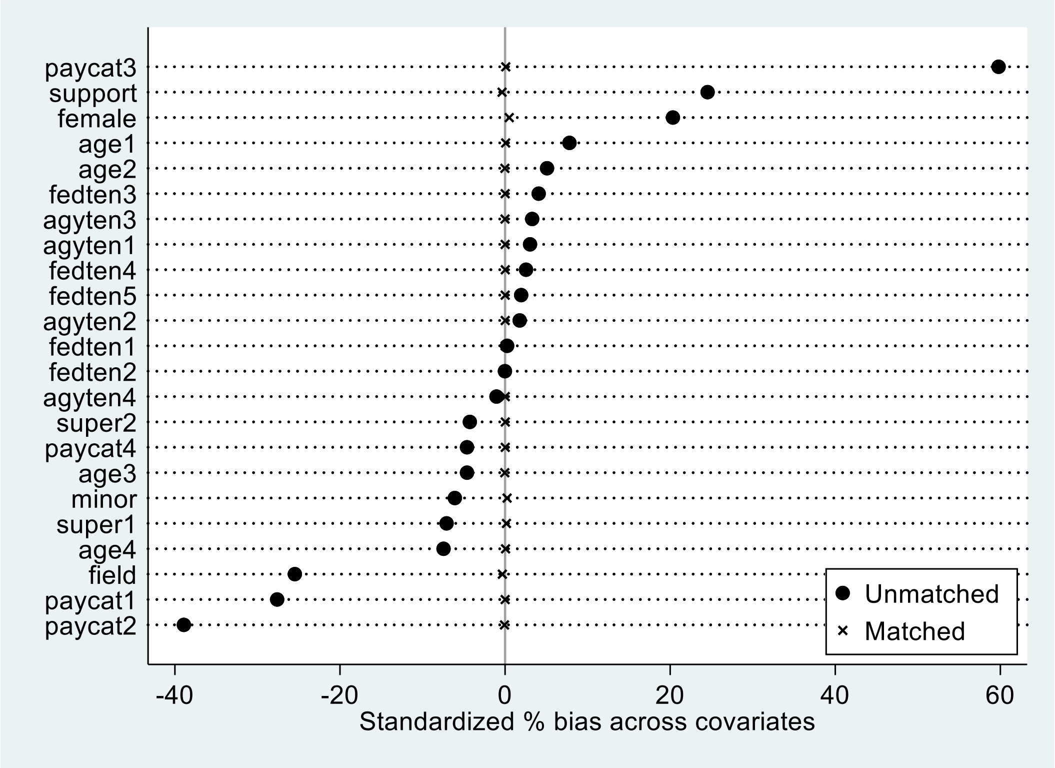
| Treatment: Telework | Job Satisfaction | | | Organizational Satisfaction | | | Affective Commitment | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATT | SE | t | ATT | SE | t | ATT | SE | t |
| Regression with Covariates | -0.016 | 0.005 | -3.45 | -0.013 | 0.005 | -2.76 | -0.002 | 0.005 | -0.34 |
| MDM Nearest Neighbor (1:1 with replacement) | -0.023 | 0.024 | -0.94 | -0.034 | 0.024 | -1.41 | -0.004 | 0.029 | -0.12 |
| PSM Nearest Neighbor (1:1 with replacement) | 0.013 | 0.034 | 0.40 | -0.028 | 0.033 | -0.85 | 0.013 | 0.033 | 0.40 |
| PSM Nearest Neighbor (1:1 without replacement) | -0.001 | 0.005 | -0.09 | 0.002 | 0.005 | 0.31 | 0.010 | 0.005 | 1.76 |
| PSM Caliper Matching (0.001) | 0.014 | 0.034 | 0.41 | -0.028 | 0.033 | -0.84 | 0.014 | 0.033 | 0.40 |

| Treatment: Alternative Work Schedules | Job Satisfaction | | | Organizational Satisfaction | | | Affective Commitment | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATT | SE | t | ATT | SE | t | ATT | SE | t |
| Regression with Covariates | -0.032 | 0.004 | -7.46 | -0.029 | 0.004 | -6.60 | -0.037 | 0.004 | -8.40 |
| MDM Nearest Neighbor (1:1 with replacement) | -0.017 | 0.022 | -0.78 | -0.016 | 0.021 | -0.73 | -0.020 | 0.022 | -0.91 |
| PSM Nearest Neighbor (1:1 with replacement) | -0.025 | 0.031 | -0.82 | -0.007 | 0.030 | -0.24 | -0.019 | 0.030 | -0.62 |
| PSM Nearest Neighbor (1:1 without replacement) | -0.040 | 0.005 | -7.57 | -0.036 | 0.005 | -6.91 | -0.044 | 0.005 | -8.28 |
| PSM Caliper Matching (0.001) | -0.025 | 0.031 | -0.82 | -0.007 | 0.030 | -0.24 | -0.019 | 0.030 | -0.62 |

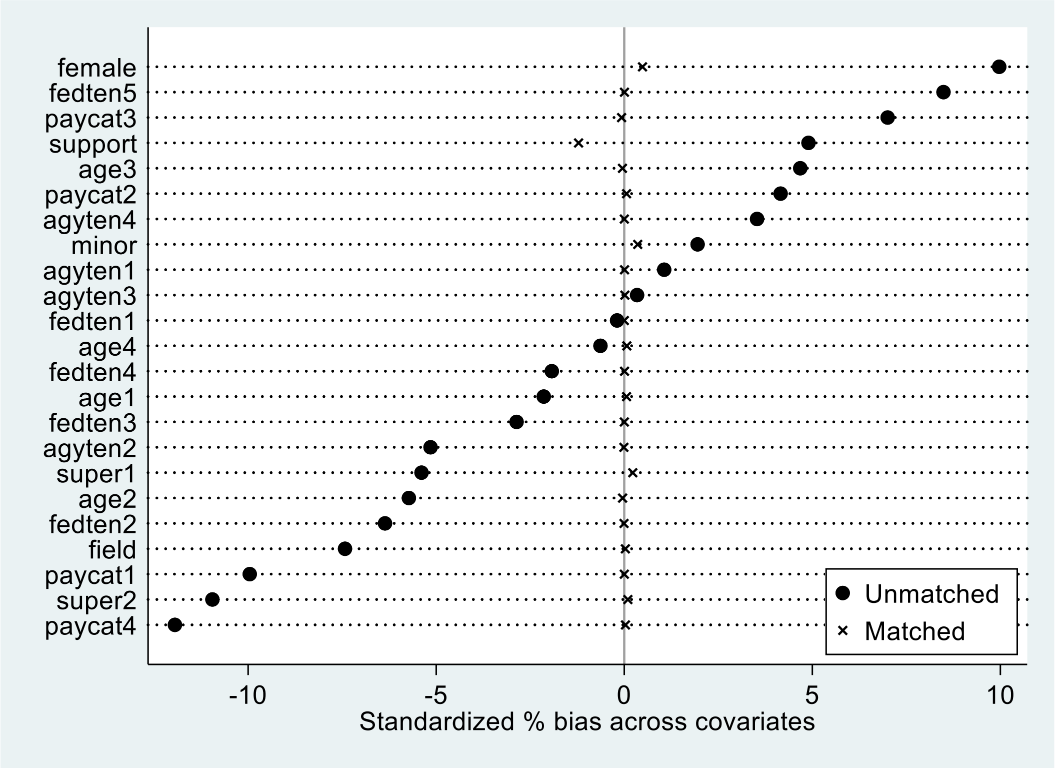
| Treatment: Child Care Programs | Job Satisfaction | | | Organizational Satisfaction | | | Affective Commitment | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATT | SE | t | ATT | SE | t | ATT | SE | t |
| Regression with Covariates | 0.087 | 0.013 | 6.68 | 0.121 | 0.013 | 9.15 | 0.103 | 0.013 | 7.82 |
| MDM Nearest Neighbor (1:1 with replacement) | 0.098 | 0.026 | 3.72 | 0.121 | 0.027 | 4.44 | 0.122 | 0.027 | 4.54 |
| PSM Nearest Neighbor (1:1 with replacement) | 0.119 | 0.033 | 3.63 | 0.161 | 0.033 | 4.90 | 0.131 | 0.033 | 3.94 |
| PSM Nearest Neighbor (1:1 without replacement) | 0.095 | 0.020 | 4.67 | 0.160 | 0.020 | 7.85 | 0.124 | 0.021 | 6.03 |
| PSM Caliper Matching (0.001) | 0.119 | 0.033 | 3.63 | 0.161 | 0.033 | 4.90 | 0.131 | 0.033 | 3.94 |

| Treatment: Elder Care Programs | Job Satisfaction | | | Organizational Satisfaction | | | Affective Commitment | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATT | SE | t | ATT | SE | t | ATT | SE | t |
| Regression with Covariates | 0.097 | 0.015 | 6.46 | 0.139 | 0.015 | 9.03 | 0.124 | 0.015 | 8.08 |
| MDM Nearest Neighbor (1:1 with replacement) | 0.094 | 0.037 | 2.52 | 0.140 | 0.034 | 4.08 | 0.070 | 0.032 | 2.22 |
| PSM Nearest Neighbor (1:1 with replacement) | 0.125 | 0.038 | 3.34 | 0.166 | 0.038 | 4.33 | 0.157 | 0.038 | 4.15 |
| PSM Nearest Neighbor (1:1 without replacement) | 0.095 | 0.024 | 4.01 | 0.183 | 0.024 | 7.58 | 0.129 | 0.024 | 5.44 |
| PSM Caliper Matching (0.001) | 0.125 | 0.038 | 3.34 | 0.166 | 0.038 | 4.33 | 0.157 | 0.038 | 4.15 |

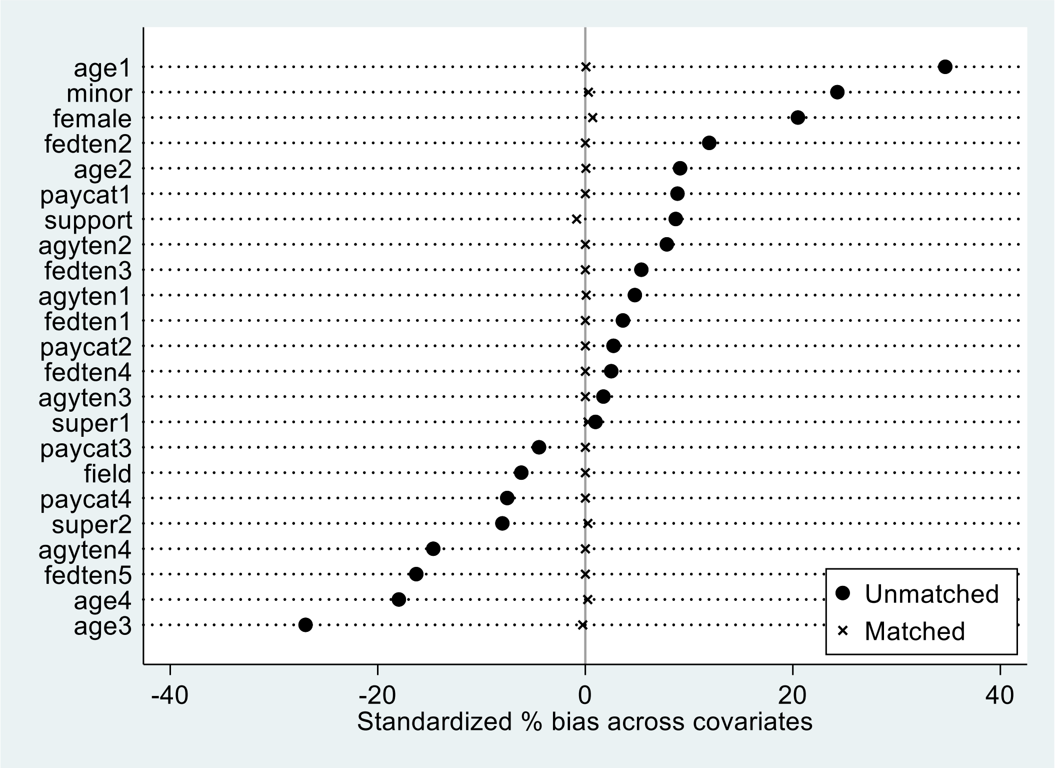
# Balance Check: Telework



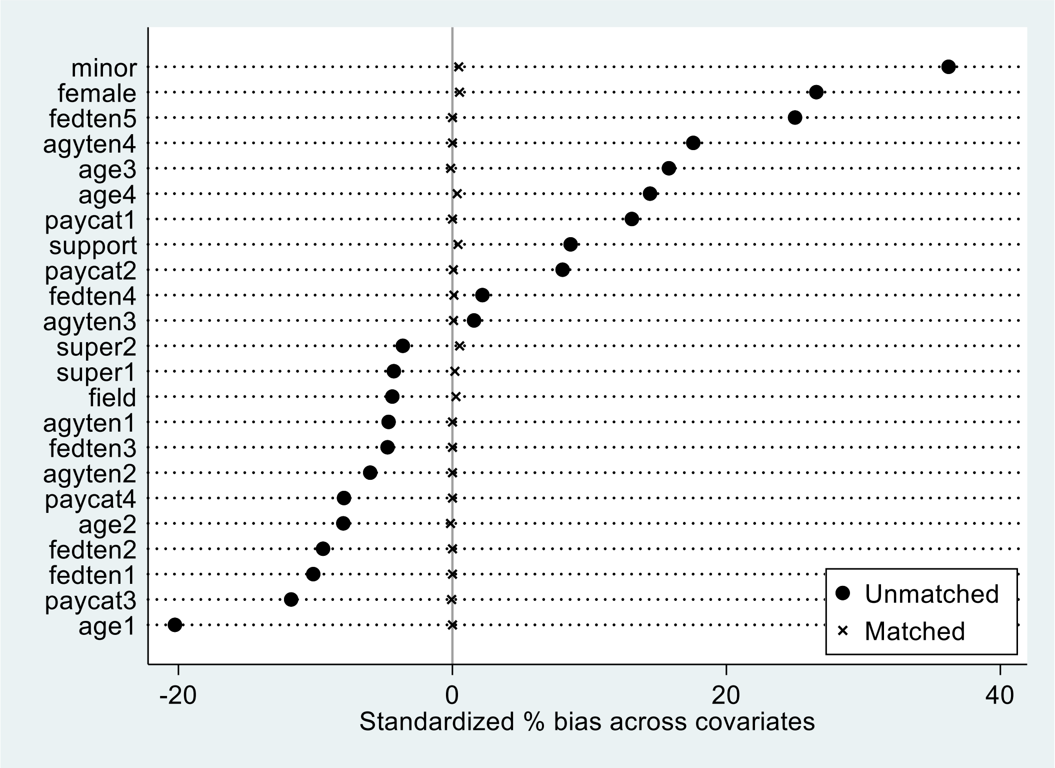
# Balance Check: Alternative Work Schedules



# Balance Check: Child Care Programs



# Balance Check: Elder Care Programs



# Telework Frequency

| | Job Satisfaction | | | Organizational Satisfaction | | | Affective Commitment | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATT | SE | t | ATT | SE | t | ATT | SE | t |
| Telework at least 3 days per week | 0.084 | 0.030 | 2.76 | 0.062 | 0.033 | 1.88 | 0.004 | 0.034 | 0.10 |
| Telework at least 1 day per week | -0.027 | 0.028 | -0.96 | -0.006 | 0.027 | -0.22 | -0.053 | 0.028 | -1.89 |
| Telework at least 1 day per month | -0.017 | 0.030 | -0.55 | -0.025 | 0.039 | -0.64 | -0.045 | 0.031 | -1.45 |
| Telework at least on a short-term basis | -0.023 | 0.024 | -0.94 | -0.034 | 0.024 | -1.41 | -0.004 | 0.029 | -0.12 |

# Implications

- We expand the existing conceptualization of WLPs by proposing two different types of WLPs.
- Our study is one of the first to empirically examine the potential differential effects of WLPs based on their orientations in work and nonwork domains.
- The findings provide additional insight into the social exchange framework by suggesting different types of WLPs may generate dissimilar levels of social exchanges between employee and organization.

# Limitations & Future Research Direction

- More observable covariates to be incorporated in the matching process for causal inference
- Potential negative consequences of certain types of WLPs
- Successful implementation and utilization of WLPs

# Questions & Feedback

Sun Young Kim (kimsun@uga.edu)

David Lee (lee211@hawaii.edu)