SUPPLEMENTAL ONLINE APPENDIX

For **Locked In? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers**

Natarajan Balasubramanian, Syracuse University
Jin Woo Chang, University of Michigan
Mariko Sakakibara, University of California, Los Angeles
Jagadeesh Sivadasan, University of Michigan
Evan Starr, University of Maryland

Appendix A. Triple Differences Exploiting Cross-Sectional Variation in Enforceability

As discussed in Section 3.3.1, a key identification assumption is that state-level variables other than CNC enforceability do not impact tech workers differentially. As an alternative, we make a narrower assumption, that highest income workers within tech are likely to be differentially impacted by CNC enforceability. This is motivated by the fact that the top executives are the most likely to have access to confidential product, client or supplier information and have developed client or supplier relationships, and hence are likely to be the bigger threat if they join competitors. This assumption is consistent with anecdotal evidence on court cases related to CNC disputes of technology companies which often involve top executives (e.g., Amazon (in 2017) sued the VP of its Amazon Web Services (AWS) team after he moved to a rival firm called Smartsheet; and earlier (in 2014) sued a key executive, AWS strategic partnerships manager, per a news article in Geekwire in June 2017. The Wall Street journal covered a 2005 case involved Microsoft suing to block Kai-Fu Lee, a former Microsoft Vice President from joining Google; one of Microsoft's lawyers was quoted saying that "Dr Lee has knowledge of trade and confidential information about our search technology and our search competitive strategy.").[1] With this assumption, we can use a specification that allows omitted factors to have different effects across sectors:

$$Y_{jks} = \alpha + \beta R_s + \gamma CNC_s + \phi R_s \times I\{Tech\}_k + \delta CNC_s \times I\{Tech\}_k$$
$$+\eta CNC_s \times I\{Tech\}_k \times I\{HighInitWage\}_j + e_{ks}$$

where j represents job spell, k represents sector, and s denotes the states, CNC_s denotes the enforceability index for state s,$I\{Tech\}_k$ denotes an indicator variable for the sector k belonging to "Technology Employers" per our definition of the technology sector (as discussed in Section 3.3.1), and $I\{HighInitWage\}_j$ is a dummy indicator for the starting wage of the job spell being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. With this specification, we can include state X sector fixed effects, flexibly allowing for other state-level variables to impact technology sector wages and mobility. In addition to the parameter η which yields the differential impact of CNC enforceability on the highest wage workers within the tech sector, the fully saturated triple difference specification we use yields other parameters of interest as discussed below. In addition to allowing for state X sector effects, another motivation to focus on the highest earners is that the sample we use in the baseline analysis is all workers (with >35K annual earnings), which may include many non-science and engineering workers, and so our baseline estimates may be diluted by inclusion of workers who may actually not be science and engineering occupations targeted by CNCs. The highest earner group within technology employers may therefore provide a better group to look at, in terms of having a higher likelihood of CNC provisions being actually enforced against them.

The fully saturated" econometric specification is:

$$Y_{ijkls} = \alpha + \beta_1 CNC_s * I\{Tech\}_k * I\{HighInitWage\}_j + \beta_2 CNC_s * I\{Tech\}_k$$
$$+\beta_3 CNC_s * I\{HighInitWage\}_j + \Sigma_s + FE(i,j,k,l) + \gamma FB_i + \varepsilon_{ijs} (A1)$$

The high wage indicator variable is as defined above, and all the other indices and terms are as described for Equation (1) in Section 3.3.2. Other possible interactions (e.g. $I\{HighInitWage\}_j * I\{Tech\}_k$) are suppressed because they are explicitly absorbed by the included fixed effects. Our coefficients of interest capturing differential effects of CNC enforceability are: (i) $\beta_1 + \beta_3$, which is the differential effect for high-initial-wage jobs compared with low-initial-wage jobs, within high-tech jobs, (ii) β_1, (corresponding to ηin the discussion above) which is a pseudo difference-in-difference-in-differences (DDD) effect of CNC enforceability for high initial wage high-tech jobs relative to low initial wage high-tech jobs, after differencing out similar difference between high-initial-wage jobs and low-initial-wage jobs in the non-tech sector, and (iii) $\beta_1 + \beta_2$, which is the effect for high-tech jobs compared with non-tech jobs, within high-initial-wage jobs. In some specifications, instead of just state fixed effects (Σ_s), we include stateX sector (Σ_{sk}) fixed effects (Tables A4 and A5).

---

[1] "Amazon sues former AWS VP over non-compete deal; Smartsheet calls claim against its new product chief an 'enormous overreach'" John Cook, Geekwire, June 11, 2017 https://www.geekwire.com/2017/amazon-sues-former-aws-vp-non-compete-deal-smartsheet-calls-claim-new-product-chief-enormous-overreach/ .
"Microsoft Sues to Keep Aide from Google", Robert A Guth, The Wall Street Journal, 2005.

In Table A1, which examines wages, we observe a persistent wage suppressing effect in all of the relevant comparisons as in Table 4. Among the high-tech jobs, the differential effect between high-initial-wage jobs and low-initial-wage jobs is estimated to be in the range of 2.9% to 5.0% throughout job tenure ($\beta_1 + \beta_3$). Among high-initial-wage jobs, enforceability is associated with a differential tech effect between 2.0% in year 4 and 2.4% in year 8 ($\beta_1 + \beta_2$). The comparison of the magnitude of the coefficients suggests that being in a high-initial-wage job is a driving factor of the wage-suppression effect. All the estimates plotted in Online Appendix Figures OA1, OA2, and OA3, show a negative effect on wages that increases over time.

In Table A2 which examines mobility, we observe results that are consistent with those in Table 6. Among the high-tech jobs, high-initial-wage jobs experience a higher likelihood of survival compared with low-initial-wage jobs throughout the job tenure by a magnitude ranging in 0.2 percentage points to 0.5 percentage points, and a longer expected job spell (by 1.4%) when enforceability scores increase by one standard deviation ($\beta_1 + \beta_3$). Within high-initial-wage jobs, enforceability has a similar effect for high-tech jobs relative to non-tech jobs, resulting in 3.5% longer job spells ($\beta_1 + \beta_2$). The large and significant pseudo DDD estimate (β_1) shows that the effect of CNC enforceability on mobility is greatest when workers are in both high-tech industry and high-initial-wage jobs. The patterns (plotted in Online Appendix Figures OA1 to OA6) suggest that the differential effect for high-initial-wage tech workers relative to low-initial-wage tech workers (Figure OA4) is relatively flat. Relative to high-initial-wage workers in non-tech sectors, however, high-initial-wage tech workers see a sharp increase in the effect on mobility over the initial few years (Figure OA5), consistent with these workers gaining appropriable capital over this period. This relative increase in the effect on mobility over the first few years of job tenure is also seen in the triple-differences in Figure OA6.

In Table A3, columns 1 through 4 show that the estimates of the differential effect on cumulative wages increase gradually over job tenure. Estimates for wage growth, presented in columns 5 through 8, show a similar trend over the job tenure, consistent with the wage estimates reported in Table 3. Table A4 and A5 include state-by-industry fixed effects and replicate the job-level wage and mobility analyses. These results, both for the within-high-tech initial wage difference term, and the triple difference term, show a negative effect on wage and mobility for the highest wage earners within tech, in line with our expectations, and broadly consistent with the baseline results.

Table A1. CNCs and Wage across Job Tenure: Sub-Samples by Industry and Initial Wage (LEHD)

This table reports the differential effect of CNC enforceability on wage throughout job tenure, across sub-samples by industry (high-tech jobs vs non-tech jobs) and initial wage (high-initial-wage jobs vs low-initial-wage jobs). High-initial-wage jobs are jobs whose starting wage is above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. The dependent variables are the log of quarterly wages at 4^{th}, …, 32^{nd} quarter of the job spell. CNC Score is measured as the 2009 CNC enforceability index scores. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log wage at xth quarter	4th qr	8th qr	12th qr	16th qr	20th qr	24th qr	28th qr	32th qr
Tech X High-initial-wage X CNC Score (β_1)	-0.0098***	-0.0085**	-0.0123***	-0.0130***	-0.0146***	-0.0145***	-0.0159***	-0.0185***
	(0.0030)	(0.0040)	(0.0040)	(0.0037)	(0.0031)	(0.0034)	(0.0028)	(0.0043)
Tech X CNC Score (β_2)	-0.0055***	-0.0064***	-0.0065***	-0.0066***	-0.0057***	-0.0051***	-0.0057***	-0.0052***
	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0015)
High-initial-wage X CNC Score (β_3)	-0.0215***	-0.0201***	-0.0196***	-0.0213***	-0.0245***	-0.0205**	-0.0246***	-0.0308***
	(0.0039)	(0.0039)	(0.0062)	(0.0068)	(0.0084)	(0.0077)	(0.0084)	(0.0100)
# of observations	10904200	7397200	5399500	4048400	3145300	2478900	1858400	1412600
R-squared	0.6726	0.6090	0.5764	0.5571	0.5430	0.5324	0.5238	0.5115
High vs Low Wage in Tech industry ($\beta_1+\beta_3$)	-0.0313***	-0.0286***	-0.0320***	-0.0343***	-0.0390***	-0.0350***	-0.0405***	-0.0493***
p value	1.52e-05	0.000279	0.00124	0.00104	7.45e-05	0.000110	5.48e-06	5.37e-07
Tech vs Non-Tech in High-initial-wage jobs ($\beta_1+\beta_2$)	-0.0152***	-0.0149***	-0.0188***	-0.0196***	-0.0203***	-0.0196***	-0.0216***	-0.0237***
p value	1.63e-05	0.000592	2.25e-05	2.44e-05	6.00e-06	2.24e-06	7.29e-07	6.16e-05
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]							
Sample	All continuing jobs in the quarter							

Table A2. CNCs and Job Duration: Sub-Samples by Industry and Initial Wage (LEHD)

This table reports the differential effect of CNC enforceability on job duration across sub-samples by industry (high-tech jobs vs non-tech jobs) and initial wage (high-initial-wage jobs vs low-initial-wage jobs). High-initial-wage jobs are jobs whose starting wage is above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. The dependent variables are dummy variables for the job spell surviving at 4^{th}, …, 32^{nd} quarter of the job spell for columns (1)-(8), and the log of length of job spells in number of quarters for column (9). CNC Score is measured as the 2009 CNC enforceability index scores. Estimation samples are all jobs that are not right censored by the quarter for columns (1)-(8), and all jobs that started its spell in year 2000 or earlier for column (9). All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Job spell survival at:	4th qr	8th qr	12th qr	16th qr	20th qr	24th qr	28th qr	32th qr	Ln(job-spell)
Tech X High-initial-wage X CNC Score (β_1)	0.0048***	0.0099***	0.0113***	0.0092***	0.0094***	0.0084***	0.0074***	0.0060***	0.0210***
	(0.0010)	(0.0019)	(0.0024)	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0038)
Tech X CNC Score (β_2)	-0.0003	0.0031**	0.0038***	0.0044***	0.0049***	0.0056***	0.0044***	0.0051***	0.0148***
	(0.0008)	(0.0011)	(0.0009)	(0.0012)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0027)
High-initial-wage X CNC Score (β_3)	0.0002	-0.0047***	-0.0059**	-0.0044***	-0.0043***	-0.0041***	-0.0040***	-0.0036***	-0.0074**
	(0.0007)	(0.0015)	(0.0022)	(0.0013)	(0.0013)	(0.0010)	(0.0008)	(0.0007)	(0.0032)
# of observations	12984300	12425700	11971100	11602500	11334900	11127400	10861700	10661700	6492100
R-squared	0.2108	0.1741	0.1732	0.1768	0.1817	0.1836	0.1831	0.1885	0.2113
High vs Low Wage in Tech industry ($\beta_1+\beta_3$)	0.00506***	0.00519***	0.00535***	0.00479***	0.00515***	0.00432***	0.00343**	0.00245*	0.0136***
p value	3.13e-06	1.18e-06	3.73e-08	3.26e-06	0.000248	0.00177	0.0141	0.0797	1.02e-05
Tech vs Non-Tech in High-initial-wage jobs ($\beta_1+\beta_2$)	0.0045***	0.0129***	0.0151***	0.0136***	0.0143***	0.0140***	0.0119***	0.0111***	0.0358***
p value	3.76e-05	6.75e-10	6.14e-07	9.60e-10	5.07e-11	4.97e-10	7.64e-08	4.89e-07	1.36e-10
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs that are not right censored by the quarter								Spell started 2000 or earlier

Table A3. CNCs and Cumulative Wages and Wage Growth over Job Tenure: Sub-Samples by Industry and Initial Wage (LEHD)

This table reports the differential effect of CNC enforceability on cumulative wage and on wage growth from initial wage throughout job tenure, across sub-samples by industry (high-tech jobs vs non-tech jobs) and initial wage (high-initial-wage jobs vs low-initial-wage jobs). High-initial-wage jobs are jobs whose starting wage is above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. The dependent variables are the log of cumulative wage at 4^{th}, 12^{th}, 20^{th}, 28^{th} quarter of the job spell for columns (1) ~ (4), and the difference between the log of quarterly wages at 4^{th}, 12^{th}, 20^{th}, 28^{th} quarter of the job spell and the log of initial wage for columns (5) ~ (8). CNC Score is measured as the 2009 CNC enforceability index scores. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent Variable	Log of cumulative wage at				Log of wage at xth quarter - Log of initial wage			
	(1) 4th quarter	(2) 12th quarter	(3) 20th quarter	(4) 28th quarter	(5) 4th quarter	(6) 12th quarter	(7) 20th quarter	(8) 28th quarter
Tech X High-initial-wage X CNC Score (β_1)	-0.0112***	-0.0095***	-0.0192***	-0.0182***	-0.0027	-0.0084***	-0.0087**	-0.0130**
	(0.0029)	(0.0034)	(0.0031)	(0.0040)	(0.0026)	(0.0030)	(0.0038)	(0.0052)
Tech X CNC Score (β_2)	-0.0057***	-0.0074***	-0.0076***	-0.0077***	-0.0054***	-0.0063***	-0.0055***	-0.0054***
	(0.0008)	(0.0006)	(0.0007)	(0.0012)	(0.0005)	(0.0008)	(0.0008)	(0.0012)
High-initial-wage X CNC Score (β_3)	-0.0186***	-0.0224***	-0.0240***	-0.0257***	-0.0136***	-0.0094***	-0.0125***	-0.0122**
	(0.0043)	(0.0063)	(0.0078)	(0.0074)	(0.0015)	(0.0023)	(0.0044)	(0.0047)
# of observations	10904000	5399000	3145000	1858000	10904000	5399000	3145000	1858000
R-squared	0.5902	0.6709	0.6892	0.6889	0.1455	0.2047	0.2504	0.2947
High vs Low Wage in Tech industry ($\beta_1+\beta_3$)	-0.0298***	-0.0319***	-0.0432***	-0.0439***	-0.0163***	-0.0178***	-0.0212***	-0.0252***
p value	2.13e-05	0.000727	9.91e-05	0.000357	7.73e-06	1.25e-05	2.21e-10	0
Tech vs Non-Tech in High-initial-wage jobs ($\beta_1+\beta_2$)	-0.0169***	-0.0169***	-0.0268***	-0.0259***	-0.00813***	-0.0146***	-0.0142***	-0.0184***
p value	3.52e-07	1.21e-05	3.23e-09	4.75e-07	0.00369	1.80e-05	0.00142	0.00197
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]							
Sample	All continuing jobs in the quarter							

Table A4. CNCs and Wage across Job Tenure: Sub-Samples by Industry and Initial Wage: State X Industry Fixed Effects (LEHD)

This table reports the differential effect of CNC enforceability on wage throughout job tenure, across sub-samples by industry (high-tech jobs vs non-tech jobs) and initial wage (high-initial-wage jobs vs low-initial-wage jobs) (dummy variable for the starting wage of the job being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes), with state-industry (2 digit NAICS code) fixed effects. The dependent variables are the log of quarterly wages at 4th, …, 32nd quarter of the job spell. CNC Score is measured as the 2009 CNC enforceability index scores. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log wage at xth quarter	4th qr	8th qr	12th qr	16th qr	20th qr	24th qr	28th qr	32th qr
Tech X High-initial-wage X CNC Score (β_1)	-0.0089***	-0.0077*	-0.0121***	-0.0124***	-0.0140***	-0.0138***	-0.0151***	-0.0185***
	(0.0030)	(0.0040)	(0.0040)	(0.0036)	(0.0031)	(0.0036)	(0.0029)	(0.0044)
Tech X CNC Score (β_2)	-0.0041***	-0.0052***	-0.0044***	-0.0047***	-0.0034***	-0.0038***	-0.0044***	-0.0079***
	(0.0006)	(0.0006)	(0.0008)	(0.0007)	(0.0005)	(0.0006)	(0.0007)	(0.0012)
High-initial-wage X CNC Score (β_3)	-0.0225***	-0.0209***	-0.0202***	-0.0224***	-0.0255***	-0.0215***	-0.0259***	-0.0314***
	(0.0038)	(0.0038)	(0.0061)	(0.0068)	(0.0085)	(0.0078)	(0.0085)	(0.0100)
# of observations	10904200	7397200	5399500	4048400	3145300	2478900	1858400	1412600
R-squared	0.6731	0.6096	0.5772	0.5580	0.5442	0.5339	0.5256	0.5135
High vs Low Wage in Tech industry ($\beta_1+\beta_3$)	-0.0315***	-0.0287***	-0.0323***	-0.0348***	-0.0395***	-0.0353***	-0.0410***	-0.0499***
p value	1.42e-05	0.000255	0.00109	0.000833	6.23e-05	0.000107	4.41e-06	4.90e-07
Tech vs Non-Tech in High-initial-wage jobs ($\beta_1+\beta_2$)	-0.0130***	-0.0130***	-0.0165***	-0.0171***	-0.0174***	-0.0176***	-0.0194***	-0.0264***
p value	4.76e-05	0.00193	0.000137	6.84e-05	5.05e-06	2.76e-05	1.02e-06	2.26e-06
Fixed Effects	[State-Industry] + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]							
Sample	All continuing jobs in the quarter							

Table A5. CNCs and Job Duration: Sub-Samples by Industry and Initial Wage: State X Industry Fixed Effects (LEHD)

This table reports the differential effect of CNC enforceability on job duration across sub-samples by industry (high-tech jobs vs non-tech jobs) and initial wage (high-initial-wage jobs vs low-initial-wage jobs) (dummy variable for the starting wage of the job being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes), with state-industry (2 digit NAICS code) fixed effects. The dependent variables are dummy variables for the job spell surviving at 4th, …, 32nd quarter of the job spell for columns (1)-(8), and the log of length of job spells in number of quarters for column (9). CNC Score is measured as the 2009 CNC enforceability index scores. Estimation samples are all jobs that are not right censored by the quarter for columns (1)-(8), and all jobs that started its spell in year 2000 or earlier for column (9). All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Job spell survival at:	4th qr	8th qr	12th qr	16th qr	20th qr	24th qr	28th qr	32th qr	Ln(job-spell)
Tech X High-initial-wage X CNC Score (β_1)	0.0050***	0.0085***	0.0096***	0.0078***	0.0081***	0.0072***	0.0064***	0.0051***	0.0185***
	(0.0010)	(0.0013)	(0.0015)	(0.0015)	(0.0017)	(0.0018)	(0.0018)	(0.0017)	(0.0037)
Tech X CNC Score (β_2)	-0.0018	-0.0009	-0.0008	0.0008	0.0008	0.0026**	0.0014	0.0021**	0.0072**
	(0.0013)	(0.0018)	(0.0016)	(0.0017)	(0.0013)	(0.0012)	(0.0013)	(0.0009)	(0.0032)
High-initial-wage X CNC Score (β_3)	-0.0001	-0.0038***	-0.0045***	-0.0034***	-0.0033***	-0.0032***	-0.0033***	-0.0028***	-0.0055*
	(0.0008)	(0.0009)	(0.0013)	(0.0010)	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0030)
# of observations	12984300	12425700	11971100	11602500	11334900	11127400	10861700	10661700	6492100
R-squared	0.2124	0.1772	0.1769	0.1802	0.1851	0.1867	0.1865	0.1916	0.2162
High vs Low Wage in Tech industry ($\beta1+\beta3$)	0.00488***	0.00464***	0.00513***	0.00440***	0.00481***	0.00404***	0.00312**	0.00233	0.0130***
p value	6.77e-06	1.93e-06	4.94e-08	8.67e-06	0.000411	0.00368	0.0261	0.101	5.34e-06
Tech vs Non-Tech in High-initial-wage jobs ($\beta1+\beta2$)	0.00315**	0.00757***	0.00884***	0.00859***	0.00893***	0.00986***	0.00785***	0.00717***	0.0257***
p value	0.0242	1.27e-05	8.71e-05	3.43e-05	2.59e-06	2.07e-06	0.000601	0.000477	5.67e-08
Fixed Effects	[State-Industry] + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs that are not right censored by the quarter								Spell started 2000 or earlier

Appendix B: Hawaii Mobility Ban -- Results from CPS Analysis

In this appendix, we use data from the Current Population Survey (CPS) to examine mobility and wage patterns before and after July 2015 in Hawaii. We place the CPS results here because the individual-level sample (particularly the technology workers sample) is relatively small, so potential bias from noise is higher here. Nevertheless, we find results that are consistent with those obtained using the QWI.

The CPS is a monthly survey given to approximately 60,000 randomly sampled households who are surveyed for 2 sets of 4 consecutive months, with a break in-between of 8 months. In each of the consecutive months, household members are asked about employer switches, while at the end of each set of interviews household members are asked about their weekly wages. To focus on full-time, working-age workers, we limit the data to those employed with a single job and between the ages of 18 and 70, and to obtain a symmetric window of pre- and post-ban trends, we limit the sample to period July 2013-July 2017.[2] While the CPS data is well-suited to study mobility of workers (by examining individual level decisions to leave their job), we caution that power is limited by the small sample size for our target population of interest (tech workers in Hawaii).[1]
For the CPS analysis, we use specifications similar to those in equations (2), (3) and (4) in the text, except for inclusion of a vector X_{it} which represents a set of time-varying individual controls including indicators for education level[3] and whether the worker is unionized, and a linear and quadratic in age and hours worked.

Figure E1 reports the trends from the CPS for the dummy indicator variable for transition from one employer to another. Consistent with the trends from the QWI, we find a significant jump in mobility soon after the ban, and a greater frequency of transitions in the post ban period, both relative to trends for other industries within Hawaii, and also relative to Tech sector in other states. Again, the results suggest the ban facilitated mobility of Tech workers. The corresponding regression results in Table 7 are very similar. There is evidence of systematically higher mobility in both the short and long run in the Within-Hawaii (Panel A) and Cross-State (Panel B) analysis, across almost all of the alternative specifications and samples. We have no mobility in CPS Tech sample in the 24 months prior to the ban, so the post-ban increases are striking; relative to the overall (across-all sectors) pre-ban mean mobility of 1.4%, the post ban increases of 4.4 percentage points (Panel A, column 2), 7.2 percentage points (Panel A, column 5), 6.5 percentage points (Panel B, column 2), and 6.6 percentage points (Panel B, column 6,) are materially large (in range of 314% to 514% increase relative to overall pre-ban mean mobility) and statistically significant as well.

In Appendix B, Table B2, the randomization inference tests show that the mobility increases observed in the CPS from the baseline DID regressions are significant at the 10% level both in the within-Hawaii analysis (columns 1 and 2) as well as for the cross-state analysis (columns 3 and 4); Table B4 confirms significance of the DDD CPS mobility results.

---

[2] Specifically, the sample is restricted to those with employment status 10 (At work) or 11 (Has job, not at work last week), and explicitly in the labor force (LABFORCE=1). We exclude multiple jobs, (i.e. use sample with multjob==1), and include only workers in the private sector (classwkr==22 (Private, for profit) or classwkr==23 (private, not for profit)). We restrict workers to age<=70 and age >=18.

[3] We collapse the various education codes in the CPS into three levels: (i) less than a bachelor's degree ("educ<=92"), (ii) bachelor's degree ("educ==111"), and (iii) more than a bachelor's degree (Masters/professional/doctorate) ("educ>111").

Figure B1. Hawaii CNC Ban and Mobility in CPS

This figure presents period-specific means (controlling for industry fixed effects in the "Within-Hawaii, Cross-Industry" graphs and for state fixed effects in the "Cross-State, Within-Tech" graphs). Data is limited to the state of Hawaii in the "Within-Hawaii, Cross-Industry" graphs (top panel), and to "Tech" industries in the "Cross-State, Within-Tech" graphs (bottom panel). "Tech" is defined as QWI 4-digit industry classifications that cover software design, development and services, to concord with the definition of "technology business" in the Hawaii statute. The dependent variable is a dummy indicator for leaving employer between month t and t+1. The group average means are weighted means, with CPS sample weights as (analytical) weights.

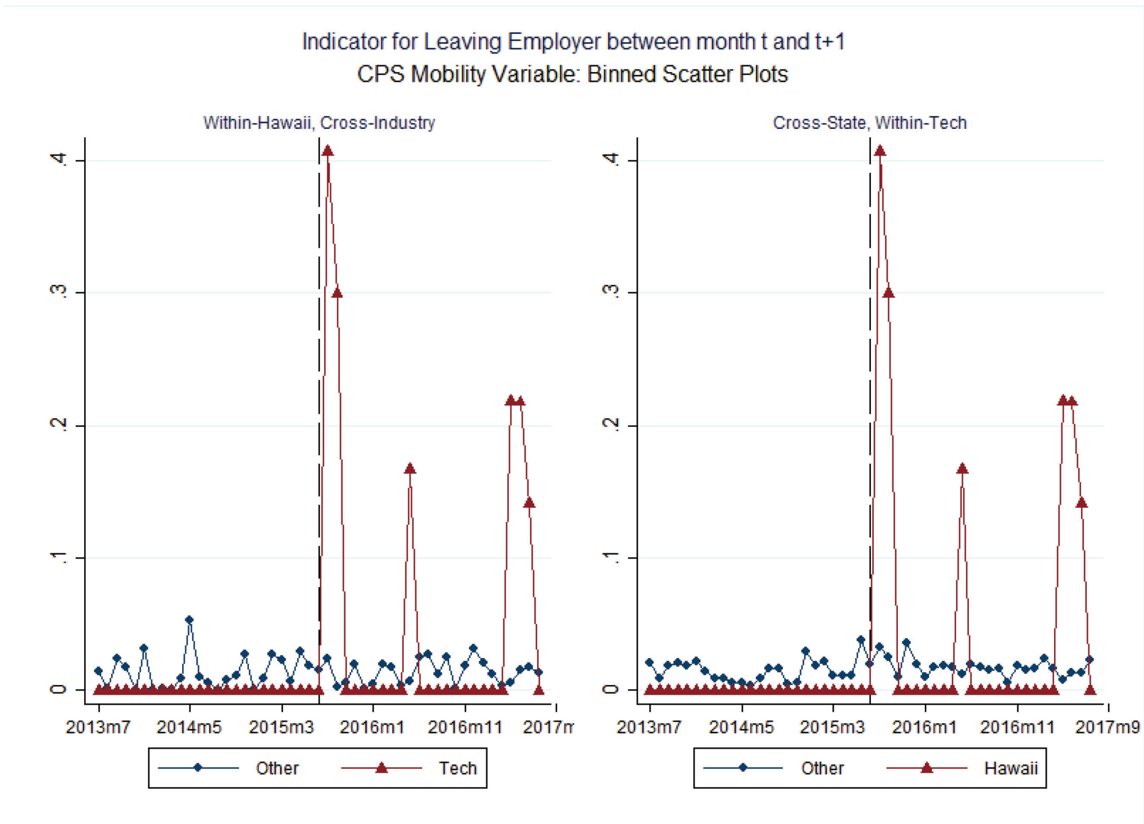


Table B1. CPS Mobility Analysis from the Hawaii Natural Experiment – Difference-in-Differences Results

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses are clustered at the industry level in Panel A and at the state level in Panel B. Data is from the CPS, July 2013 to July 2017. Data is limited to the state of Hawaii in Panel A, and to "Tech" industries in Panel B. "Tech" is defined as QWI 4-digit industry classifications that cover software design, development and services, to concord with the definition of "technology business" in the Hawaii statute. The dependent variable is a dummy indicator for leaving employer between month t and t+1. "Post" is defined as July 2015 and afterwards; SR_Post is 2015m7 to 2016m8, and LR_Post is 2016m9 to 2017m7. In Panel A, Cols 1-4 are limited to 4-digit industries within the two-digit industries that contain the tech industries, while other columns include all industries. In Panel B, Cols 1-4 are limited to the 40 states closest to Hawaii in the CNC score in absolute terms, while other columns include all states. All specifications use CPS sample weights as (analytical) weights. Number of observations adjusts for weights and singleton cells, i.e., drops zero weights and singleton-cells (when fixed effects are added). The mean (sd) of the dummy dependent variable for Tech industries in the pre-July 2015 period is 0 (0) and for the full sample in the pre-July 2015 period is 0.014 (0.115).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Cross-Industry, Within-Hawaii				
Post X Tech	0.035**	0.044**			0.073***	0.072***		
	(0.015)	(0.017)			(0.023)	(0.023)		
SR_Post X Tech			0.042	0.047*			0.080***	0.078***
			(0.025)	(0.024)			(0.014)	(0.014)
LR_Post X Tech			0.029***	0.041***			0.067**	0.067**
			(0.008)	(0.012)			(0.033)	(0.033)
# of observations	537	537	537	537	17,226	17,226	17,226	17,226
R-squared	0.298	0.308	0.298	0.308	0.047	0.049	0.047	0.049
Sample	Tech2d	Tech2d	Tech2d	Tech2d	All	All	All	All
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
				Panel B: Cross-State, Within-Tech				
Post X HI	0.055***	0.065***			0.056***	0.066***		
	(0.002)	(0.003)			(0.002)	(0.002)		
SR_Post X HI			0.056***	0.071***			0.056***	0.070***
			(0.003)	(0.004)			(0.002)	(0.003)
LR_Post X HI			0.054***	0.060***			0.055***	0.062***
			(0.003)	(0.003)			(0.002)	(0.003)
# of observations	26,181	26,178	26,181	26,178	37,104	37,100	37,104	37,100
R-squared	0.014	0.029	0.014	0.029	0.011	0.022	0.011	0.023
Sample	40 States	40 States	40 States	40 States	All	All	All	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	NA	Yes	NA	Yes	NA	Yes	NA
Year by Month FE	Yes	NA	Yes	NA	Yes	NA	Yes	NA
State FE	Yes	NA	Yes	NA	Yes	NA	Yes	NA
Ind X Year-Month	No	Yes	No	Yes	No	Yes	No	Yes
State X Ind	No	Yes	No	Yes	No	Yes	No	Yes

Table B2. CPS Mobility Analysis from the Hawaii Natural Experiment – Triple Difference Results

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses are clustered at the state level. Data is from the CPS, July 2013 to July 2017. "Tech" is defined as QWI 4-digit industry classifications that cover software design, development and services, to concord with the definition of "technology business" in the Hawaii statute. The dependent variable is a dummy indicator for leaving employer between month t and t+1. "Post" is defined as July 2015 and afterwards; SR_Post is 2015m7 to 2016m8, and LR_Post is 2016m9 to 2017m7. Cols 1-4 are limited to the 40 states closest to Hawaii in the CNC score in absolute terms, while other columns include all states. All specifications use CPS sample weights as (analytical) weights. Number of observations adjusts for weights and singleton cells, i.e., drops zero weights and singleton-cells (when fixed effects are added). The mean (sd) of the dummy dependent variable for Tech industries in the pre-July 2015 period is 0 (0) and for the full sample in the pre-July 2015 period is 0.014 (0.115).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post X HI X Tech	0.057***	0.068***			0.058***	0.069***		
	(0.002)	(0.002)			(0.002)	(0.002)		
SR_Post X HI X Tech			0.061***	0.075***			0.060***	0.074***
			(0.002)	(0.002)			(0.002)	(0.002)
LR_Post X HI X Tech			0.054***	0.062***			0.056***	0.063***
			(0.003)	(0.003)			(0.003)	(0.003)
HI X Tech	-0.012***		-0.012***		-0.013***			
	(0.001)		(0.001)		(0.001)			
Observations	899,350	899,165	899,350	899,165	1,219,093	1,218,873	1,219,093	1,218,873
R-squared	0.024	0.033	0.024	0.033	0.019	0.028	0.019	0.028
Sample	40 States	40 States	40 States	40 States	All	All	All	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Ind FE	No	Yes	No	Yes	No	Yes	No	Yes
State X Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind X Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix C. Cross-State Synthetic Control Analysis for the Hawaii Natural Experiment

In this section, we use the synthetic control approach proposed in Abadie, Diamond and Hainmueller (2010). Under this approach, the Tech sector of Hawaii is compared to a "synthetic" control composed of a weighted average combination of other states' Tech sector. To examine the statistical significance of the estimated effects, we construct the ratio of the post-treatment mean-square prediction error to the pre-treatment mean square prediction error for the Hawaii Tech sector and compare it to the same ratio for the placebo runs using other states (as in Figure 8 of Abadie Diamond and Hainmueller 2010).

In Figure C1, we find close match between the separation rate patterns for Hawaii relative to the synthetic control in the pre-ban period, but a notable upward divergence for Hawaii in the post-ban period. This divergence is notably different from placebo runs, and in fact Hawaii has the largest ratio of pre- to post-ban mean square prediction errors, leading to a p-value of 0.02 for both mobility measures. Similarly, the synthetic control analysis for the Wage measures in the QWI in Figure C2 show a close match in pre-ban trends between Hawaii and the synthetic control for both the wage variables. The log overall average wage shows a short run upward deviation relative to the synthetic control which reverses in the longer run, while the log average wage of hires shows a more persistent post-ban upward deviation for Hawaii. The p-value for the log overall average wage is 0.19, while for the log average wage of hires is 0.07. The weaker effect on overall average wage could be because wages remain sticky for workers that do not change jobs, and are impacted most for workers that are newly entering jobs.

The results for the CPS mobility variable in Figure D3 are similar to those in Figure C1, with significant increase in Hawaii in the post-ban period, and a p-value of 0.03.

Figure C1: Synthetic Control Analysis for QWI Wage Variables

The factor model uses 8, 5 and 1 period lags (prior to the quarter of the ban) of the variable itself, and same lags for overall separation rate as observed covariates. The bottom panel reports the distribution of the ratio of pre- to post-ban mean square prediction errors, with the red vertical line indicating the estimate for Hawaii.

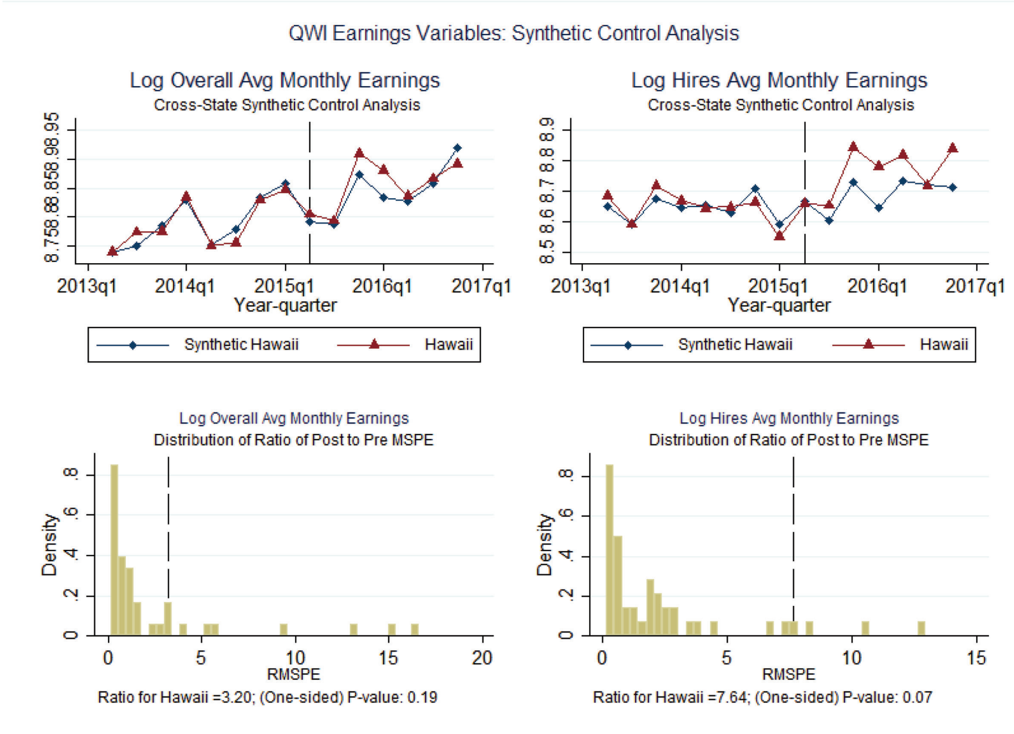


Figure C2: Synthetic Control Analysis for QWI Mobility Variables

The factor model uses 8, 5, and 1 period lags (prior to quarter of the ban) of the variable itself, and same lags for Log Hires Average Monthly Earnings as observed covariates. The bottom panel reports the distribution of the ratio of pre- to post-ban mean square prediction errors, with the red vertical line indicating the estimate for Hawaii.

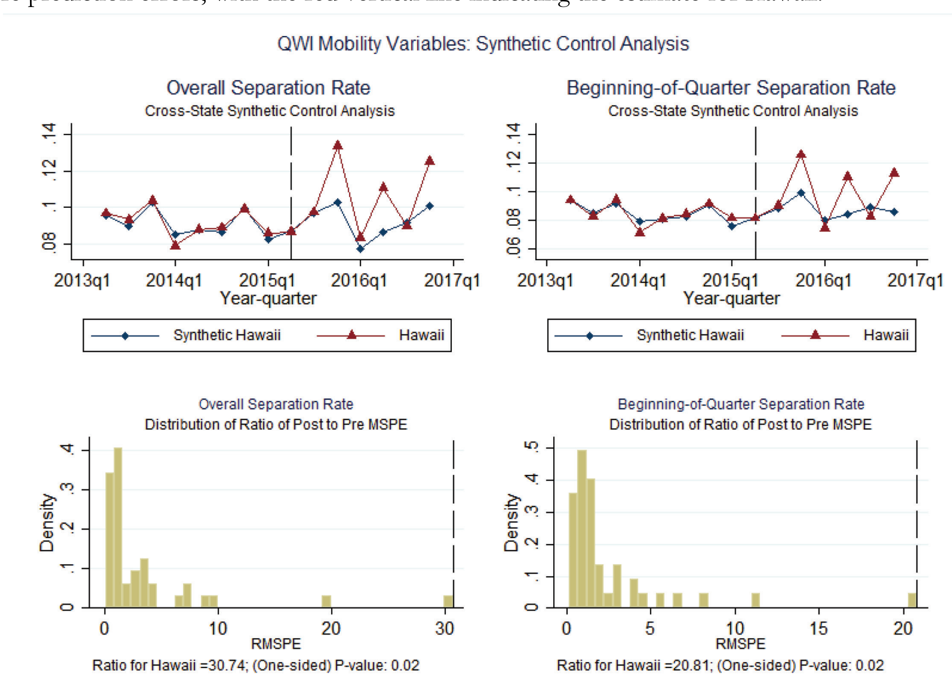
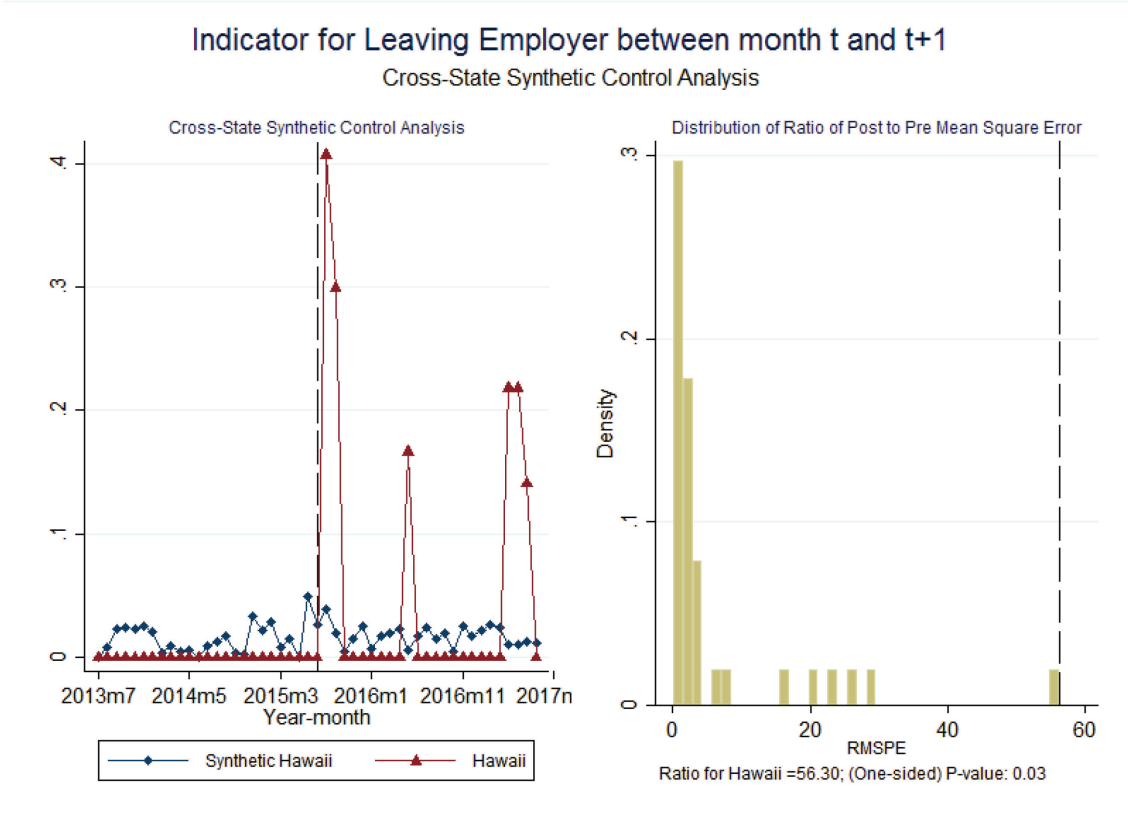


Figure C3: Synthetic Control Analysis for CPS Mobility Variable
The factor model uses 21, 12 and 1 period lags (prior to the month of ban) of the period mean of the dummy indicator for leaving employer between month t and t+1 for the Tech sector. The bottom panel reports the distribution of the ratio of pre- to post-ban mean square prediction errors, with the red vertical line indicating the estimate for Hawaii.



Appendix D. Randomization Inference for the Hawaii Natural Experiment

In this section, we use permutation tests (Hess 2017) to assess the robustness of our Hawaii results. In particular, to assess the significance of the within-state, cross-industry results, we randomly assign the Tech dummy to the same fraction of sectors as in the baseline analysis, clustering by 4-digit NAICS so that all observations in the industry are assigned the same value for the dummy, and then run our main difference-in-differences analysis within the full sample of the QWI or CPS for 500 replications. Similarly, we assign the ban "treatment" to a random state across 500 replications. We then compare the point estimates for Post*Tech (for within-state) and Post*HI (for the cross-state) in the baseline estimate relative to the estimates from the 500 replications, and examine (one-sided) p values (reported in brackets); that is the permutation tests generate p values as the proportion of replications with estimates greater than that in the baseline estimation.

Table D1 reports results for the specifications using QWI variables in Columns 3, 4 and 7, 8 of Tables 1 and 2. For the Triple Difference Analysis, alternative randomization inferences could be possible (e.g., across states, across industries or across state-industry combinations). Because tech-specific year shocks seemed to us the most significant concern, we undertook a randomization test by randomizing the "ban" treatment across states (like in the Cross-state analysis), with 500 replications. Table D2 reports specifications using QWI variables in Columns 3, 4 and 7, 8 of Table 3.

Table D3 and Table D4 reports permutation test results using the CPS mobility variable for specifications in column 6 and 8 of Table B1 and Table B2 respectively.

Overall, in most cases the statistical significance we obtain here for the QWI analysis are lower than what we get from standard inference in Tables 1, 2 and 3, but are fairly consistent in most cases in terms of significance at a 10% cutoff level. In particular, we get significance at the 10% level in the cross-state for increase in earnings and mobility (Table D1 column 3). The triple difference results are significant in column 1 of Table D1 at the 5% level for all variables except overall wage (row 1). All of the CPS mobility results are significant at the 10% level (all triple difference results at the 1% level). In all tables, we have *** p<0.01, ** p<0.05, * p<0.1

Table D1: DID Analysis of QWI Mobility and Wage variables -- Baseline estimates and P-values (one-sided) from Randomization Inference (Fisher Permutation) tests

	Within-Hawaii, Cross-Industry			Cross-State, Within-Tech		
	(1)	(2)		(3)	(4)	
	Post	SR_Post	LR_Post	Post	SR_Post	LR_Post
Earnings variables						
	-0.005	0.003	-0.021	0.018*	0.018	0.017
Log Overall Average Monthly Earnings	[0.482]	[0.348]	[0.646]	[0.086]	[0.162]	[0.224]
Log Hires Average Monthly Earnings	0.026	0.044	-0.012	0.071**	0.078*	0.058*
	[0.230]	[0.160]	[0.458]	[0.014]	[0.062]	[0.078]
Mobility variables						
Overall Separation Rate	0.003	0.008	-0.007	0.011**	0.014**	0.007
	[0.354]	[0.154]	[0.608]	[0.026]	[0.022]	[0.116]
Beginning-of-Quarter Separation Rate	0.004	0.010*	-0.009	0.011**	0.014**	0.005
	[0.308]	[0.088]	[0.622]	[0.016]	[0.022]	[0.222]

Table D2: Triple Difference Analysis of QWI Mobility and Wage variables -- Baseline estimates and P-values (one-sided) from Randomization Inference (Fisher Permutation) tests

	(1)	(2)	
	Post	SR_Post	LR_Post
Earnings variables			
Log Overall Average Monthly Earnings	0.0071	0.0100	0.0010
	[0.263]	[0.21]	[0.343]
Log Hires Average Monthly Earnings	0.0424**	0.0548**	0.0166
	[0.04]	[0.02]	[0.232]
Mobility variables			
Overall Separation Rate	0.00979**	0.01124***	0.00676
	[0.012]	[0.002]	[0.178]
Beginning-of-Quarter Separation Rate	0.0096**	0.0126***	0.0034
	[0.014]	[0.002]	[0.251]

Table D3: DID Analysis of CPS Mobility variable -- Baseline estimates and P-values (one-sided) from Randomization Inference (Fisher Permutation) tests

	Within-Hawaii, Cross-Industry			Cross-State, Within-Tech		
	(1)	(2)		(3)	(4)	
	Post	SR_Post	LR_Post	Post	SR_Post	LR_Post
Indicator for leaving employer between month t and t+1	0.061***	0.072**	0.053**	0.028**	0.033**	0.024*
	[0.004]	[0.016]	[0.010]	[0.014]	[0.028]	[0.088]

Table D4: Triple Difference Analysis of CPS Mobility variable -- Baseline estimates and P-values (one-sided) from Randomization Inference (Fisher Permutation) tests

	(1)	(2)	
	Post	SR_Post	LR_Post
Indicator for leaving employer between month t and t+1	0.0686***	0.0741***	0.0634**
	[0.002]	[0.002]	[0.002]

Appendix E. Online Theory Appendix

We present a simple framework that illustrates that although job-lock (as manifested in lower mobility and wages) resulting from high CNC enforceability is a distinct possibility under plausible assumptions, wages may in fact not be lower, particularly if firm investments are important for match value, and even mobility may not be lower if worker investments are very important for match value. Thus, ultimately, whether or not CNC enforceability decreases worker mobility and wages is an empirical question.

We use a simple model of mobility and wage determination that simplifies and draws on key features of Cahuc, Postel-Vinay and Robin (2006) and Burdett and Mortensen (1998). We abstract from cross-worker and cross-firm heterogeneity, and extend the model to allow for endogenous determination of worker-firm "match surplus" (or relationship value). The match surplus generated by the worker is θ. At the beginning of the period the worker searches for opportunities outside the firm, and receives a single offer with wage W_0, from a uniform distribution $[0,1+\mu]$.The worker derives utility only from wages, so worker's decision rule is as follows:[4]

- If $W_0 > \theta$: Exit the firm and take outside offer
- If $W_0 \leq \theta$: Negotiate with the firm

The negotiated wage if the worker stays in the firm equals the outside wage offer plus a share of the surplus (see Cahuc et al, equation 2):[5]

$$\text{W (if stay)} = \text{Outside Option} + \alpha\,(\text{Match Surplus}) = \text{W}_0 + \alpha(\theta - \text{W}_0)$$

where α reflects bargaining power of the workers, so when $\alpha = 1$, the workers get paid the full value of the relationship. (We discuss the effect of CNCs on α below.)

If the outside wage is greater than θ, the worker leaves. So the probability of exit is determined by the probability of getting an offer above θ, which in turn is set by where θ is relative to the upper bound of outside offers $1 + \mu$:

$$\text{P[Exit]} = \text{P}[W_0 > \theta] = 1 - \frac{\theta}{1+\mu} \quad (1)$$

Expected wages conditional on staying (which correspond to our regressions estimates, assuming independent distributions and wage draws over time and across workers) is a linear combination of outside wage offers and match surplus within the firm:[6]

$$\text{E[W|Stay]} = \text{E[Outside Option]} + \alpha\text{E[Match Surplus]} = \text{E}[\text{W}_0|\text{W}_0 \leq \theta] + \alpha(\theta - \text{E}[\text{W}_0|\text{W}_0 \leq \theta])$$
$$= \frac{\theta}{2} + \alpha\left(\theta - \frac{\theta}{2}\right) = \frac{(1+\alpha)\theta}{2} \quad (2)$$

$$\text{E[W|Exit]} = (\text{E}[\text{W}_0|\text{W}_0 > \theta]) = \frac{(1+\mu)+\theta}{2}$$

$$\text{E[W]} = \text{P[Stay]E[W|Stay]} + \text{P[Exit]E[W|Exit]}$$
$$= P[W_0 \leq \theta]\,(\alpha\,\theta + (1-\alpha)E[W_0\,|W_0 \leq \theta]) + P[W_0 > \theta](E[W_0\,|W_0 > \theta])$$
$$= \frac{\theta}{1+\mu}\left(\frac{(1+\alpha)\theta}{2}\right) + \left(1 - \frac{\theta}{1+\mu}\right)\left(\frac{(1+\mu)+\theta}{2}\right) = \left[\frac{1+\mu}{2} + \frac{\alpha\theta^2}{2(1+\mu)}\right] \quad (3)$$

The expected wages and the probability of exiting the firm are illustrated in Figure TA1 below.

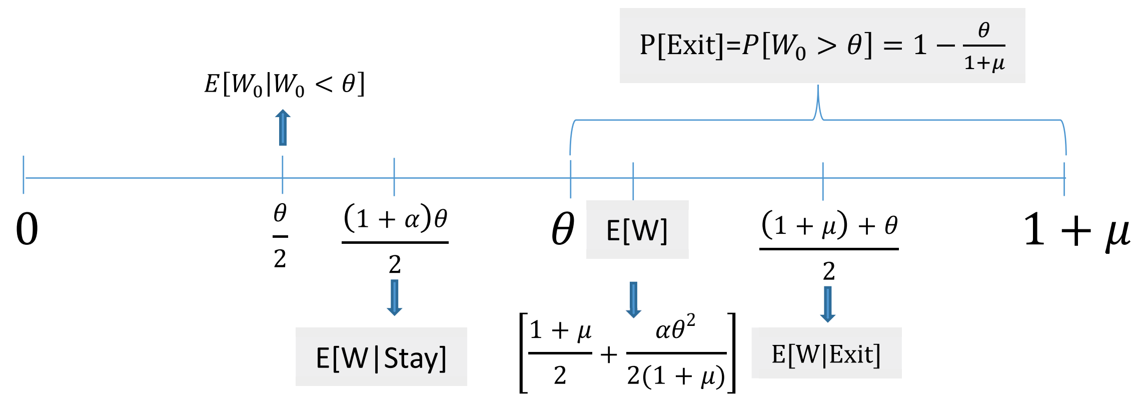
---

[4] To focus on CNC enforceability, our framework abstracts from other drivers of worker turnover including e.g., health shocks, spousal career shocks, or learning about match quality. This is innocuous so long as these are uncorrelated with degree of CNC enforceability (or adequately controlled for in our empirical analysis).

[5] Cahuc et al (2006) show a dynamic version of the negotiated wage to be the outcome of a strategic bargaining game based on Rubinstein's (1982) alternating offers game.

[6] In particular, within job spell wage regressions correspond to E[Wage|stay] and worker career regressions correspond to the unconditional expected wage E[Wage].

Figure TA1: Expected wages, and probability of exit



<u>Assumptions about effects of CNC enforceability</u>:

A0: A basic maintained assumption we make is that frictions make it costly to avoid enforceability by moving across states, and that firms cannot pre-commit to wages.[7]

We make two other fairly straightforward assumptions about the effects of non-compete enforceability (η):

A1: Increase in enforceability leads to reduction in worker bargaining power, i.e., $\frac{d\alpha}{d\eta} < 0$, and

A2: The upper bound of outside wage distribution is decreasing in enforceability, i.e., $\frac{d\mu}{d\eta} < 0$.

Assumption A1 is motivated by a widely discussed potential effect of CNC covenants (e.g., Arnow-Richman 2006). Assumption A2 tractably captures two plausible effects of CNC enforceability. First, the firms that can derive the highest value from the worker are likely to be close competitors who can exploit all of the worker's knowledge; so increase in CNC enforceability may induce some of the highest value outside bidders to drop out of bidding for the worker. Second, while we assume for tractability that the worker obtains one outside offer, in a more general case the worker may get multiple (say N) bids so that the relevant outside option is the maximum of N bids. Increase in CNC enforceability would likely decrease the number of firms willing to bid for the worker, which would decrease the expected maximum of the bids.[8]

We consider three alternative cases for the determination of the match surplus (or relationship value) θ.

<u>**Case 1: Exogenous $\boldsymbol{\theta}$**</u>

In this case, by assumption the relationship-specific value does not vary with degree of CNC enforceability. However, by assumptionsA1 and A2 above, the worker bargaining power and outside wage offer range varies leading to the following results:

---

[7] Black and Loewenstein (1991) show that in a model with moving costs, if firms can commit to wages for the entire length of the employee's tenure, then there is no deviation from frictionless competitive market outcomes, as the firm and workers can negotiate upfront and prevent ex-post hold-up problems (Boal and Ransom, 1997). Our next two assumptions implicitly capture the outcome in Black and Loewenstein that when firms cannot commit, firms will enjoy monopsony power (which would increase with CNC enforceability) over incumbent workers whenever wages come up for renegotiation. If workers anticipate this, then the ex-post hold-up could be offset with front-loaded wages, so that the wage-tenure profile shows a downward slope. While the lower slope in high enforceability regions is consistent with our empirical results, we find no evidence that the initial wage levels are positively correlated with higher enforceability (see Table OA7).

[8] This can be seen analytically in the case where the underlying wage distribution is a Gumbel with location and scale parameters ϕ and σ; then expected maximum of N draws = $\phi + \sigma \log(N)$. In a continuous time model as in Cahuc et al (2006), the notion would be that CNC enforceability dampens inter-firm competition by reducing the arrival rate of outside offers.

Result 1: Probability of exit goes down with increase in CNC enforceability.

Result 2a: $E[W|Stay]$ *(i.e., average wage conditional on staying in the initial job spell) goes down with increase in CNC enforceability.*

Result 2b: $E[W]$ *(i.e., unconditional average wage) goes down with increase in CNC enforceability.*

Result 1 follows directly from assumption A2, as decrease in μ reduces the probability that the outside offer will exceed the relationship-specific value (see Equation 1). Similarly, reduction in worker bargaining power (assumption A1) leads immediately to Result 2a (see Equation 2). Result 2b, follows from the fact that in Equation (3), both E[W|Exit] and E[W|Stay] go down, and weight on the larger (E[W|Exit]) also goes down (as P[Exit] goes up).

Case 2: Endogenous θ, firm and individual investments matter for relationship value

Suppose θ is endogenous and determined by firm investments(k) and individual investments (m), such that $\theta^2 = \mathrm{a}k + \mathrm{b}m - \frac{\mathrm{c}k^2}{2} - \frac{\mathrm{d}m^2}{2}$

Firm and individual investments are made ex-ante, based on expectations. The firm's optimization problem is:

$$\max_k E[\Pi] = \max_k \{\mathrm{P[stay]}(\theta - \mathrm{E[W|stay]}) - \mathrm{k}\} = \max_k \left\{\left(\frac{\theta}{1+\mu}\right)\left(\theta - \left(\frac{1+\alpha}{2}\right)\theta\right) - k\right\}$$

$$= \max_k \left(\left(\frac{1-\alpha}{2(1+\mu)}\right)\theta^2 - k\right)$$

The individual's optimization problem is: $\max_m E[\mathrm{Surplus}] = \max_m \{\mathrm{E[W]}) - \mathrm{m}\}$

$$= \max_m \left\{\left[\frac{1+\mu}{2} + \frac{\alpha\theta^2}{2(1+\mu)}\right] - m\right\}$$

This yields optimal investment choices:

$$k^* = \frac{1}{c}\left(\mathrm{a} - \frac{2(1+\mu)}{(1-\alpha)}\right); m^* = \frac{1}{d}\left(\mathrm{b} - \frac{2(1+\mu)}{\alpha}\right) \tag{3}$$

Lemma 1a: Optimal investment (k^**) is unambiguously increasing in degree of CNC enforceability (as* μ *and* α *both decrease with CNC enforceability).*

Lemma 1b: Optimal investment (m^**) is decreasing in degree of CNC enforceability so long as* $\frac{d\alpha}{d\eta} < \frac{\alpha}{1+\mu}\frac{d\mu}{d\eta}$ *(or* $\left|\frac{d\alpha}{d\eta}\right| > \frac{\alpha}{1+\mu}\left|\frac{d\mu}{d\eta}\right|$ *).*

For firms, the negative effects on both the bargaining and outside options increase investment incentives in high enforceability regimes. For individuals, the negative bargaining effect lowers investment incentive in high enforceability regimes, but the decrease in outside option increases the incentive to invest to increase relationship-specific value, so the net effect of an increase in CNC enforceability on individual investment is negative only if the magnitude of enforceability's effect on bargaining power is strong enough. Hereafter, to focus on the interesting case of varying implications for individual and firm investment we will assume A3: $\frac{d\alpha}{d\eta} < \frac{\alpha}{1+\mu}\frac{d\mu}{d\eta}$. i.e., $\left|\frac{d\alpha}{d\eta}\right| > \frac{\alpha}{1+\mu}\left|\frac{d\mu}{d\eta}\right|$.

Solving out for optimal relationship capital yields:

$$\theta^* = \left[\frac{a^2}{2c} - \frac{2\,(1+\mu)^2}{c(1-\alpha)^2} + \frac{b^2}{2d} - \frac{2\,(1+\mu)^2}{d\,\alpha^2}\right]^{0.5} \tag{4}$$

We now consider two polar cases, to understand differences in outcomes depending on whether firm or individual investments matter for relationship-specific value.

Case 2A: Only firm investments matter (i.e., b=d=0)

In equation 4, the third and fourth terms drop out, and we get the following results:

Result 3: Probability of exit is unambiguously decreasing in CNC enforceability.

This follows from the facts that optimal investment (Lemma 1a), and hence relationship capital level θ increases with enforceability (in equation 4, μ and α decrease with increase in enforceability), and the upper bound μ drops (by assumption A1).

Result 4a: Effect of increased enforceability on $E[W|Stay]$ (i.e., average wage conditional on staying in the initial job spell) is ambiguous.

This is because in equation 2, while θ increases with CNC enforceability, bargaining power α declines, so the net impact on the wages is unclear. Intuitively, the relationship-specific value is enhanced but workers' bargaining power may be lowered so much that they may not get any net benefit.

Result 4b: Effect of increased enforceability on $E[W]$ (i.e., unconditional average wage) is ambiguous.

This is because in equation 3, effect on both E[W|Exit] and E[W|stay] is unclear, though weight on larger quantity (E[W|Exit]) (i.e., probability of exit) does go down (from Result 3 above).

Case 2B: Only individual investments matter (i.e., a=c=0)

In equation 4 the first and second terms drop out, and we get the following results:

Result 5: Effect of CNC enforceability on probability of exit is ambiguous; if $\frac{d\theta^*}{d\eta} > \frac{\theta^*}{1+\mu}\frac{d\mu}{d\eta}$ $(i.e., if\ \left|\frac{d\theta^*}{d\eta}\right| < \frac{\theta^*}{1+\mu}\left|\frac{d\mu}{d\eta}\right|$) then probability of exit declines with enforceability.

This follows from the facts that while optimal investment (Lemma 1a), and hence relationship capital level θ decreases with enforceability (this is guaranteed by assumption A3, which makes $\frac{d\theta^*}{d\eta} < 0$), the upper bound μ drops (by assumption A1). Thus the net effect depends on which shift is larger; only if the magnitude of the decline in optimal relationship value is small enough relative to magnitude of the decline in the upper bound will the probability of exit decline with enforceability.

Result 6a: $E[W|Stay]$ (i.e., average wage conditional on staying in the initial job spell) decreases with increase in enforceability.

This is because in equation 2, both θ and bargaining power α declines with enforceability. Intuitively, relationship value and bargaining power being lower means workers are worse off.

Result 6b: Effect of increased enforceability on $E[W]$ (i.e., unconditional average wage) is ambiguous in general, but if probability of exit is declining with enforceability, then $E[W]$ also declines with enforceability.

This is because in equation 3, both E[W|Exit] and E[W|Stay] decrease with enforceability, but weight on larger quantity (E[W|Exit]) may <u>increase</u> (if P[Exit] goes up). If P[Exit] goes down (i.e., if shift in upper bound μ is modest relative to the shift in θ^*), then then the ambiguity is resolved and E[W] declines with enforceability.

<u>Summary of Cases</u>

When θ is exogenously determined (that is, individual or firm investments in human capital do not affect θ), increasing enforceability does not affect θ, but the maximum possible wage offer, $1 + \mu$, decreases. This decreases the probability of exit, thus decreasing worker mobility. Furthermore, because α decreases, average wages also decrease. We refer to the decline in mobility concurrent with a reduction in wages as the "lock-in" effect of enforceability.[9]

However, when θ is affected by the level of investments made by the firm or worker, the effects are not uniformly unambiguous. As we show in the appendix, increasing CNC enforceability increases the firm's investment and decreases the worker's investments in human capital. In the case where human capital responds only to firm investment, higher CNC enforceability increases the probability that the worker stays but the effect on wages is ambiguous. This is because higher CNC enforceability increases the firm's investment in θ, which increases the threshold wage for the worker to leave. Since the upper bound of outside offers $(1 + \mu)$ falls, the probability of leaving (and worker mobility) declines unambiguously. If higher enforceability does not affect the bargaining power significantly, then the increased human capital from higher firm investments implies higher wages for workers.

[9] We want to note that in the health economics literature (e.g., Gruber and Madrian, 1994), the term "job-lock" is used to refer only to lower mobility from lack of portability of health insurance across jobs. In our model and discussion in this paper, we use the term lock-in to indicate a reduction in mobility accompanied by a reduction in wages. That is, we use "lock-in" to indicate harmful outcome for workers where reduced mobility (and hence potentially lower utility from forgoing outside opportunities) is not offset by any increase in wages.

However, if higher enforceability significantly reduces workers' bargaining power, their wages may decline. This would be consistent with workers being "locked in."

In the case where human capital responds only to the worker's investment, both the mobility and wage effects of increasing enforceability are ambiguous. θ decreases due to decreased individual investment, but so does the upper bound of outside offers. Wages within the firm, conditional on staying, unambiguously decrease due to decreased worker bargaining power and decreased worker investment, but average wage levels may not decrease if the probability of leaving and accepting an outside wage offer increases.

Endogeneity of enforceability choice by the firm

The above analysis presumes that increase in enforceability results in decline of bargaining power (A1) and decrease in upper bound of outside offers (A2). In principle however, firms could choose not to include CNC clauses even in high-enforceability regimes; this raises the question of whether it would be the case that excluding CNC clauses may be beneficial to the firm. The following lemmas address this.

Lemma 2a: In case 2A (where firm investments matter for relationship-specific value), it is in the firm's interest to fully exploit enforceability, i.e., firm surplus is greater with enforcing (and reducing bargaining power (A1) and outside offers (A2)) than without.

Lemma 2b: In case 2B (where individual investments matter for relationship-specific value), sufficient conditions for the firm to fully exploit enforceability are that (i) probability of exit declines in enforceability, and (ii) $\frac{d\theta^*}{d\eta} > \frac{\theta^*}{1-\alpha}\frac{d\alpha}{d\eta}(i.e., \left|\frac{d\theta^*}{d\eta}\right| < \frac{\theta^*}{1-\alpha}\left|\frac{d\alpha}{d\eta}\right|$ *)*

Lemma 2a follows directly from taking a simple derivative of firm's optimal profit levels with respect to η and verifying that higher enforceability (η) in case 2A leads to greater profits. Lemma 2b follows form the fact that if probability of exit is lower, and if decline in bargaining power of the worker is steep enough, then the firm's share of the smaller pie (due to reduced worker investment) is larger with enforceability than without.

Note that in an incomplete information environment, A1 and A2 do not depend on *formal* inclusion of CNC clauses in employment contracts. In particular, if there are some firm types for whom Lemma 2a and/or 2b holds, and if outside bidders are unsure of the target worker's employer firm type, A2 would bind as bids would be more discouraged as enforceability increases. Similarly, if employees have incomplete information on whether CNC clauses are included in the contract (they may often be unaware of clauses in the contract e.g. Arnow-Richman 2006) or if they fear these could be introduced, that may be sufficient to reduce bargaining power, and make A1 bind as well.

References

Rubinstein, Ariel. 1982. "Perfect equilibrium in a bargaining model." *Econometrica*: 97-109.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean Robin. 2006. "Wage Bargaining With On-The-Job Search: Theory and Evidence," *Econometrica*, Vol. 74, No. 2 (March, 2006), 323-364.

Appendix F: Additional Figures and Tables

Figure OA1. CNCs and Wage of High-Tech Jobs: High-initial-wage Jobs vs Low-initial-wage Jobs (LEHD)

This figure plots the coefficient estimates and the 95% confidence intervals of the differential effect of CNC enforceability on wage, of high-initial-wage jobs relative to low-initial-wage jobs within high-tech jobs. High-initial-wage jobs are defined as jobs with starting wage being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. Wage is the log of quarterly wage at 4th, …, 32nd quarter of the job spell.

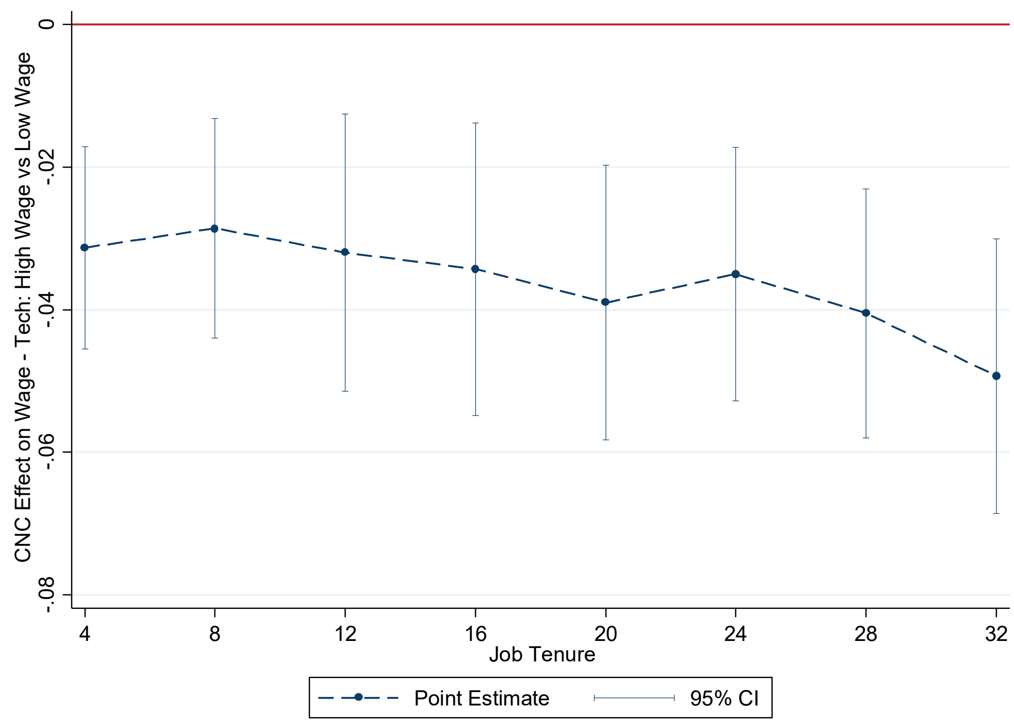


Figure OA2. CNCs and Wage of High-initial-wage Jobs: High-Tech Jobs vs Non-Tech Jobs (LEHD)

This figure plots the coefficient estimates and the 95% confidence intervals of the differential effect of CNC enforceability on wage, of high-tech jobs relative to non-tech jobs within high-initial-wage jobs. High-initial-wage jobs are defined as jobs with starting wage being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. Wage is the log of quarterly wage at 4th , …, 32nd quarter of the job spell.

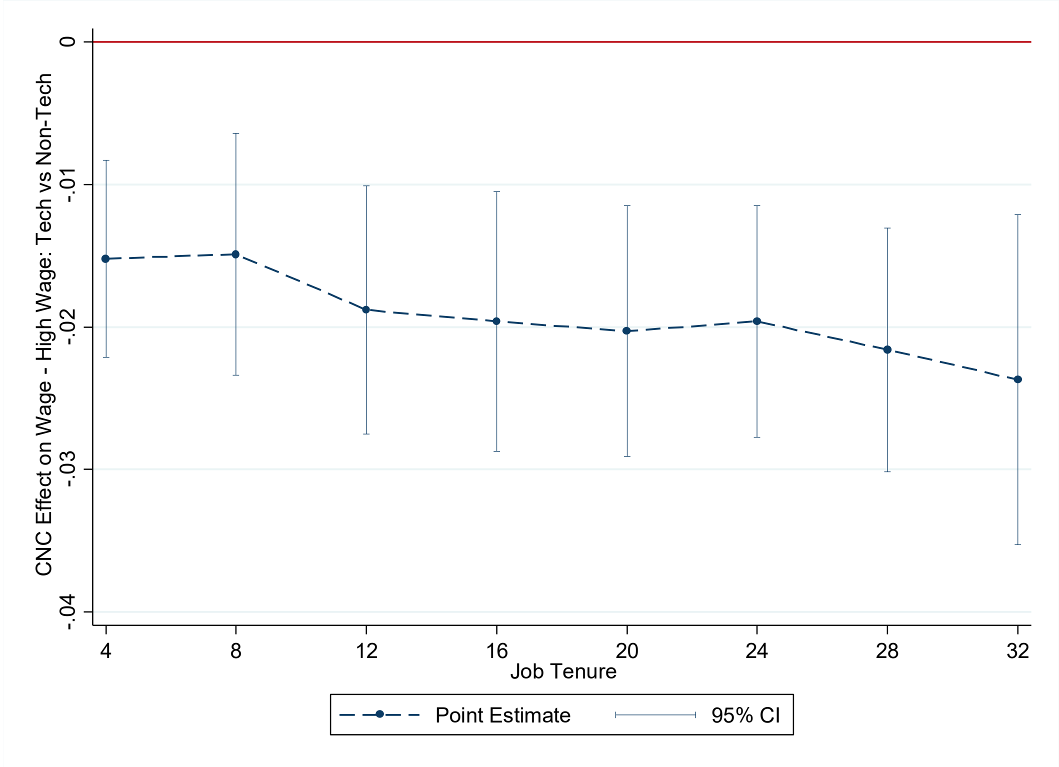


Figure OA3. Pseudo Difference-in-Difference-in-Differences: CNCs and Wage of High-Tech Jobs (LEHD)

This figure plots the coefficient estimates and the 95% confidence intervals of the pseudo difference-in-difference-in-differences effect of CNC enforceability on wage, of high-tech jobs relative to non-tech jobs, after differencing out the common unobservables across high-initial-wage jobs and low-initial-wage jobs. High-initial-wage jobs are defined as jobs with starting wage being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. Wage is the log of quarterly wage at 4th, …, 32nd quarter of the job spell.

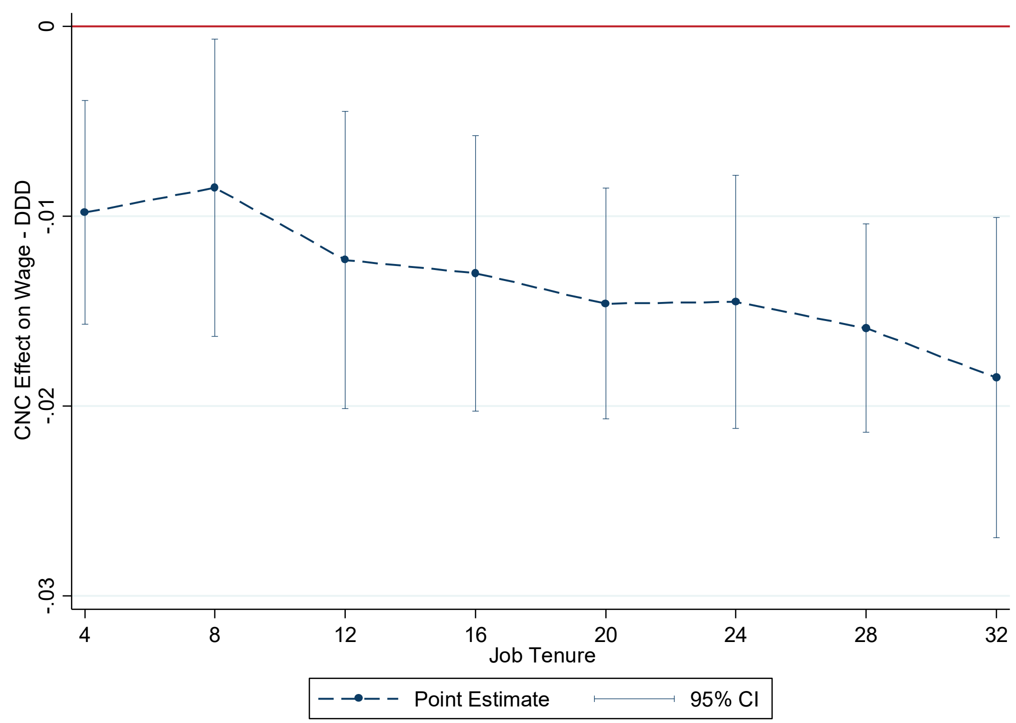


Figure OA4. CNCs and Job Duration of High-Tech Jobs: High-initial-wage Jobs vs Low-initial-wage Jobs (LEHD)
This figure plots the coefficient estimates and the 95% confidence intervals of the differential effect of CNC enforceability on job duration, of high-initial-wage jobs relative to low-initial-wage jobs within high-tech jobs. High-initial-wage jobs are defined as jobs with starting wage being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. Mobility is measured as the dummy variable for the spell surviving at 4th, …, 32nd quarter of the job spell.

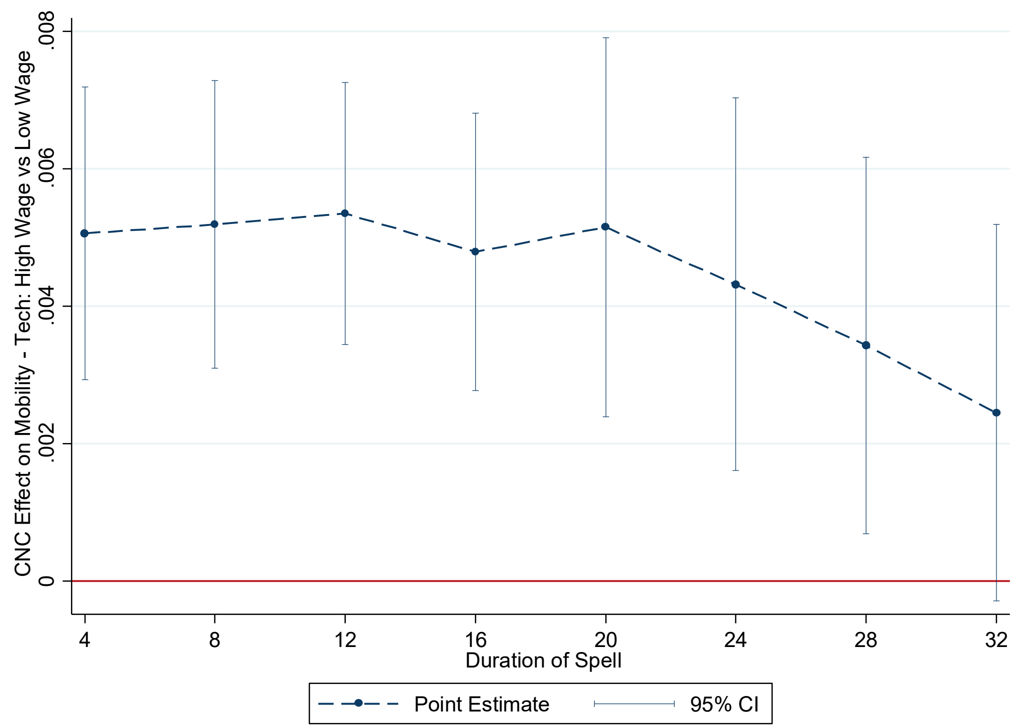


Figure OA5. CNCs and Job Duration of High-initial-wage Jobs: High-Tech Jobs vs Non-Tech Jobs (LEHD)

This figure plots the coefficient estimates and the 95% confidence intervals of the differential effect of CNC enforceability on job duration, of high-tech jobs relative to non-tech jobs within high-initial-wage jobs. High-initial-wage jobs are defined as jobs with starting wage being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. Mobility is measured as the dummy variable for the spell surviving at 4th, …, 32nd quarter of the job spell.

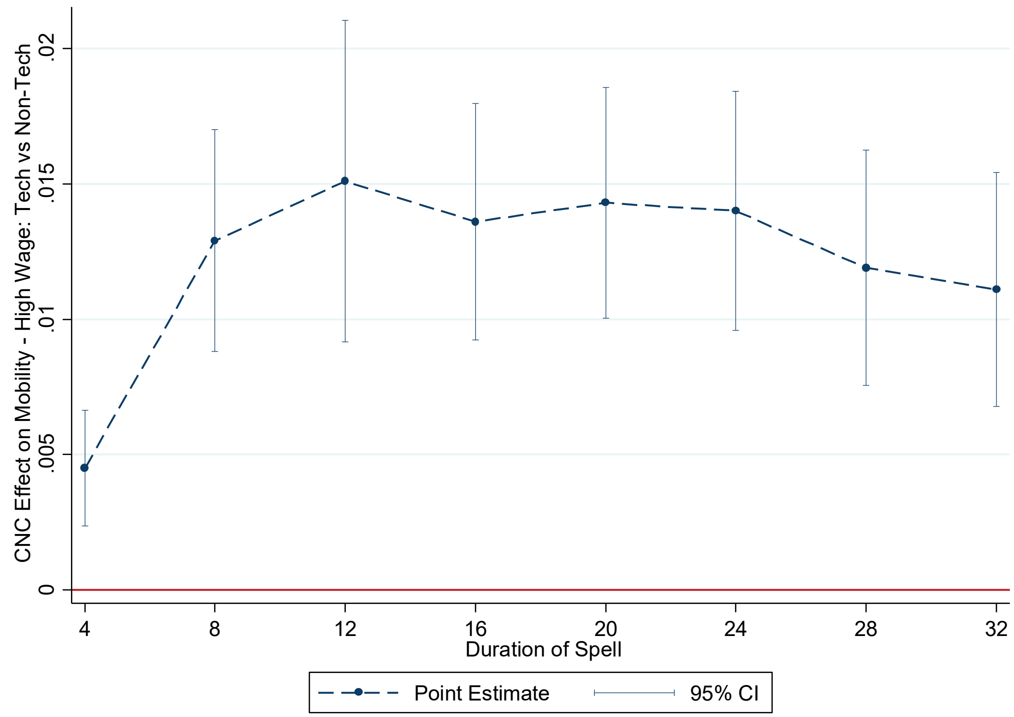


Figure OA6. Pseudo Difference-in-Difference-in-Differences: CNCs and Job Duration of High-Tech Jobs (LEHD)
This figure plots the coefficient estimates and the 95% confidence intervals of the pseudo difference-in-difference-in-differences effect of CNC enforceability on job duration, of high-tech jobs relative to non-tech jobs, after differencing out the common unobservables across high-initial-wage jobs and low-initial-wage jobs. High-initial-wage jobs are defined as jobs with starting wage being above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. Mobility is measured as the dummy variable for the spell surviving at 4th, …, 32nd quarter of the job spell.

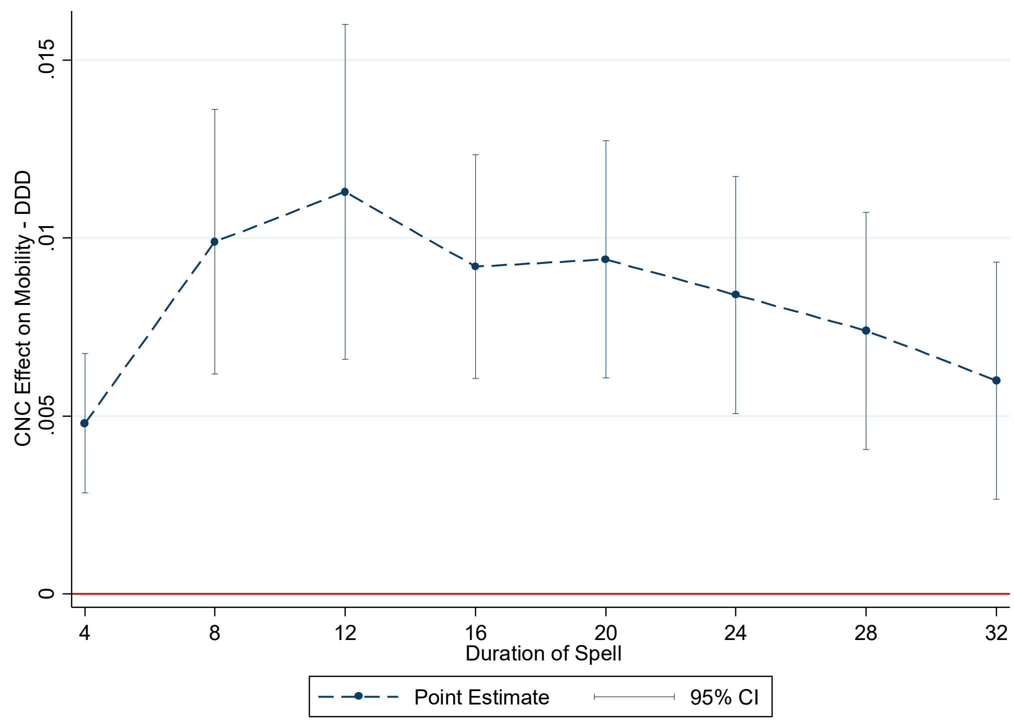


Figure OA7: Rank and Raw Correlation between Starr (2019) and Bishara (2011) CNC Enforceability Measures for 2009
The Starr (2019) index is a modification of the Bishara (2011) index of CNC enforceability. While Bishara (2011) weighted seven features of local noncompete enforceability regulation using his judgment of the relative importance of different factors, Starr (2019) used a factor analysis approach to weight the seven dimensions used in Bishara (2011).The weights generated by the factor analysis are surprisingly consistent with the weights used by Bishara (2011), so the two measures are highly correlated.

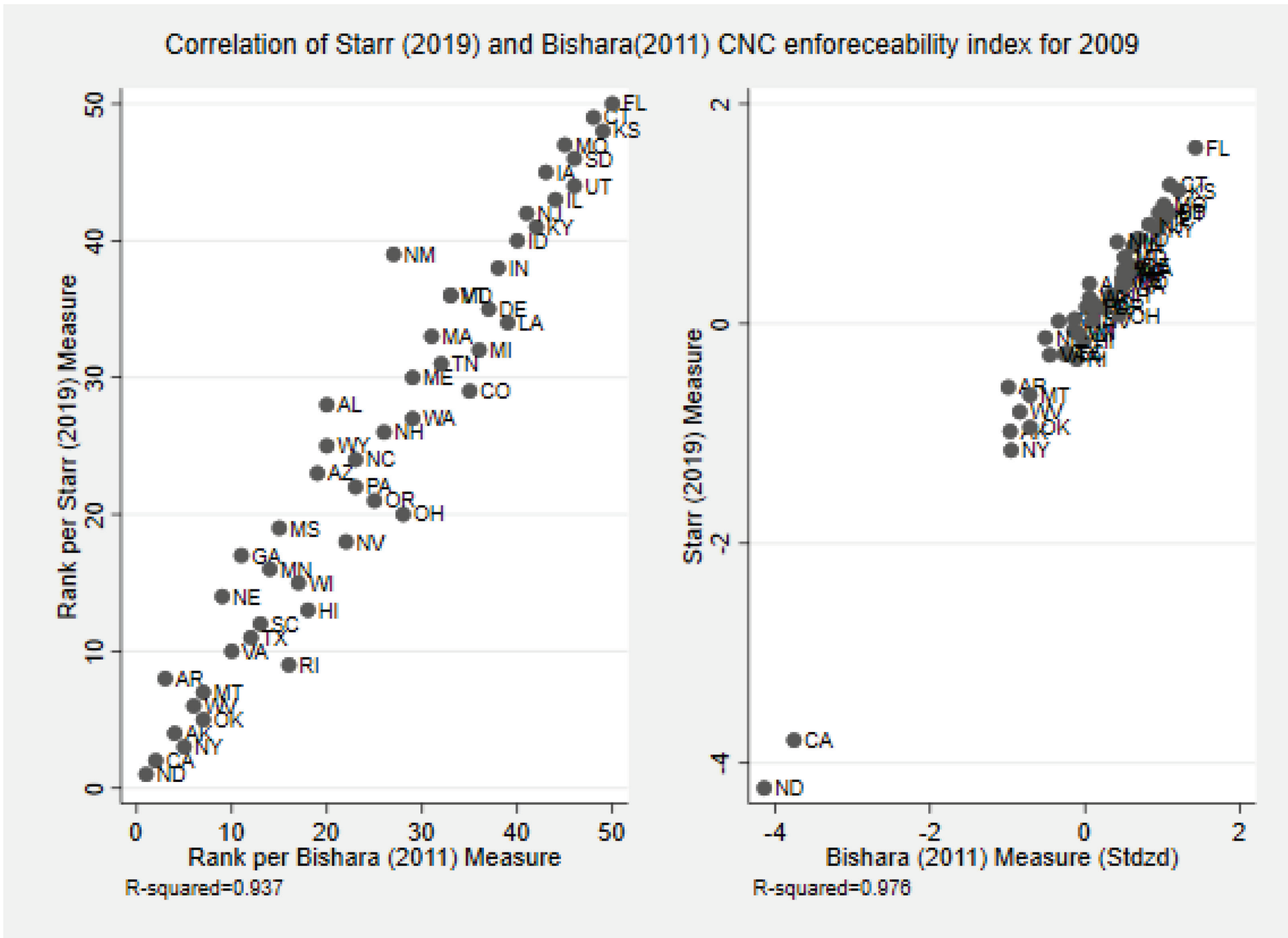


Figure OA8: Geography of Non-Compete Enforceability in 2009

This map presents a geographic heat map of the Starr (2019) index of CNC enforceability (used in this paper), with lighter shades representing weaker CNC enforceability and darker shades representing stronger enforceability.

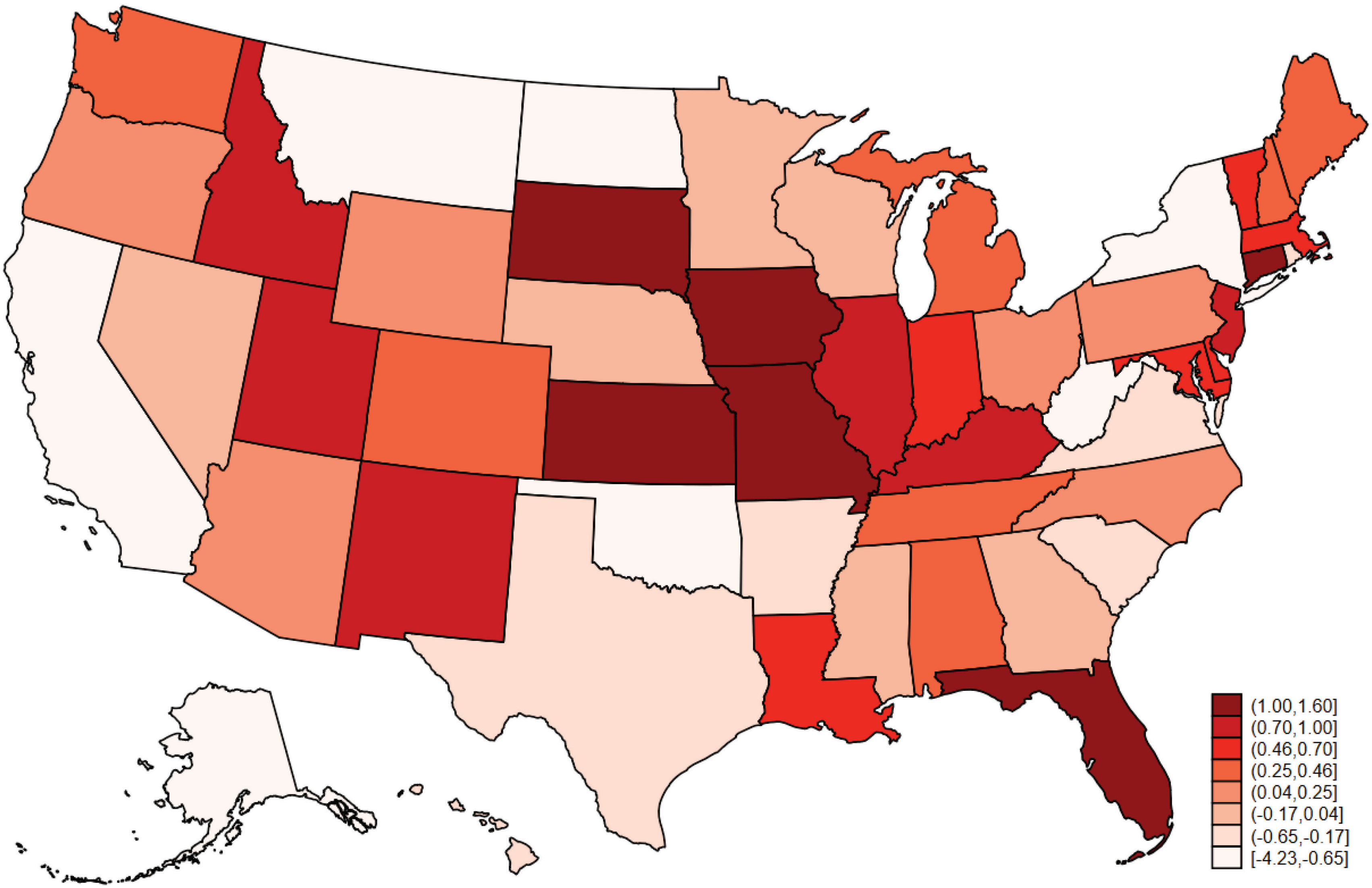


Figure OA9: Correlation between CNC Enforceability Index (Starr 2019) and Other State-Level Variables (GDP per capita, Corporate Taxes, Union Density and State Labor Regulations)

See Table OA12 for regression table version of these scatter plots. State GDP per capita is in year 2000 USD and is for based on BEA data. Top corporate state tax rate is for year 2000.Union membership density for 2000 is from http://www.unionstats.com. Right to Work is a dummy variable for states that passed right to work (anti-union) legislation as at year 2000. Implied contract exception, public policy exception and good faith exception are dummy variables for these three exceptions to the employment-at-will doctrine, for year 1999, taken from Autor, Donohue and Schwab (2006).

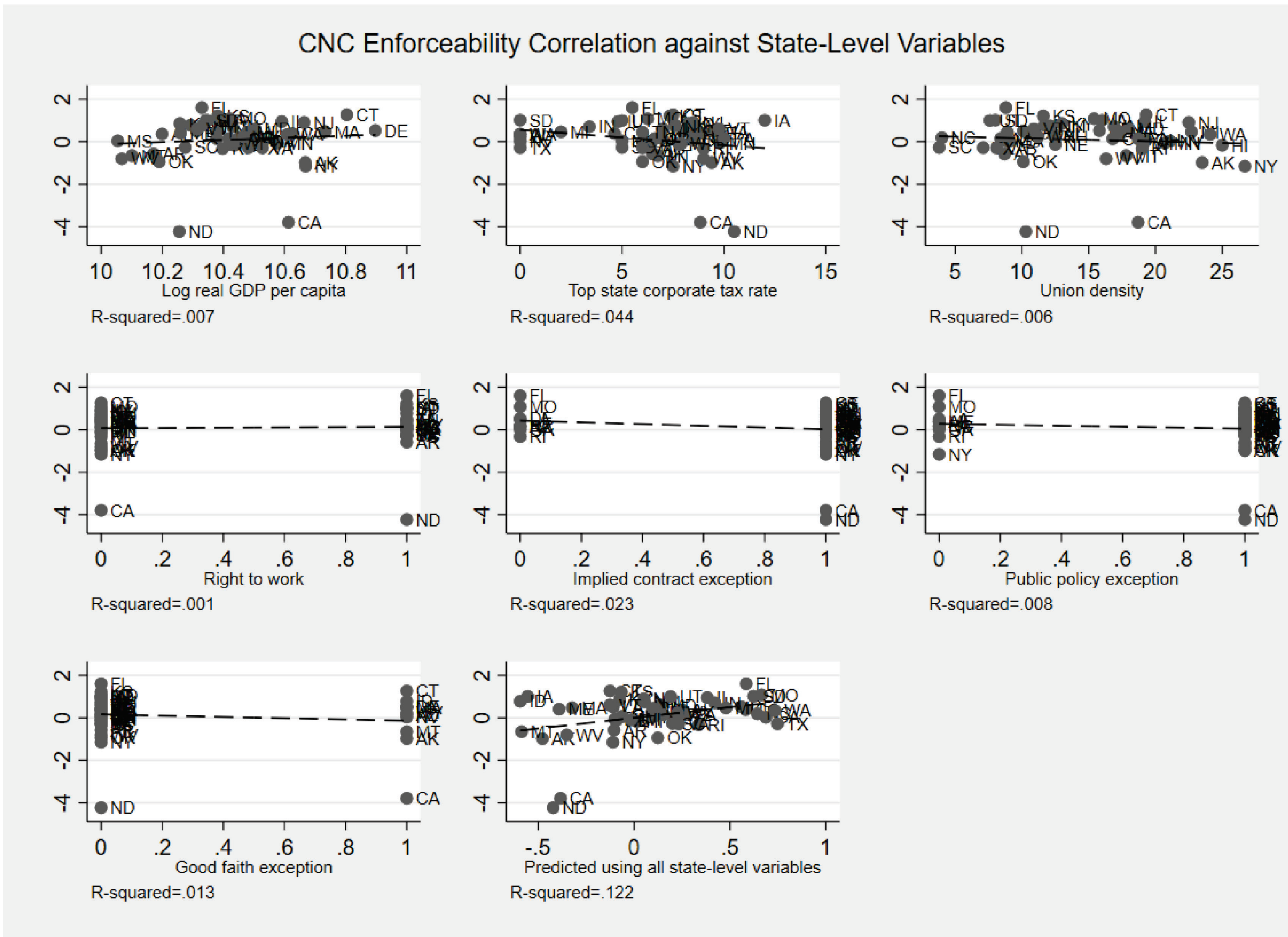


Table OA1. QWI Hawaii Ban Analysis – Summary statistics of Dependent Variables

This table presents the period specific means and standard deviations for the four outcome variables. Data is from the QWI, 2013Q2 to 2017Q1. Data is limited to the state of Hawaii in Panel A, and to "Tech" industries in Panel B. "Tech" is defined as QWI 4-digit industry classifications that cover software design, development and services, to concord with the definition of "technology business" in the Hawaii statute. The Overall Separation Rate defined as All Separations (i.e., Sep) divided by Employment in the Reference Quarter (i.e., EmpTotal). The Beginning-of-Quarter separation rate (i.e., SepBegR). "Post" is defined as July 2015 and afterwards; Panel A is limited to 4-digit industries within Hawaii; Panel B, is limited to tech sectors in all states. The statistics are weighted using Beginning-of-quarter Employment (Emp) as (analytical) weights. Parentheses indicate negative values.

			Log Overall Average Monthly Earnings	Log Hires Average Monthly Earnings	Overall Separation Rate	Beginning-of-Quarter Separation Rate
Panel A: Cross-Industry, Within-Hawaii						
Pre-July 2015	Non-Tech	N	2,032	1,968	1,972	2,030
		Mean	8.076	7.714	0.125	0.107
		SD	0.440	0.475	0.064	0.055
	Tech	N	27	27	26	27
		Mean	8.788	8.636	0.091	0.085
		SD	0.084	0.139	0.020	0.025
Post-July2015	Non-Tech	N	1,352	1,309	1,307	1,350
		Mean	8.156	7.806	0.139	0.119
		SD	0.440	0.466	0.066	0.060
	Tech	N	19	18	19	19
		Mean	8.862	8.775	0.107	0.100
		SD	0.064	0.154	0.022	0.024
Pre-diff (tech – non-tech)			0.71	0.92	(0.03)	(0.02)
Post-diff (tech – non-tech)			0.71	0.97	(0.03)	(0.02)
DID of raw means			(0.01)	0.05	0.00	0.00
Panel B: Cross-State, Within-Tech						
Pre-July 2015	Non-HI	N	2,830	2,783	2,771	2,829
		Mean	9.054	8.770	0.086	0.078
		SD	0.286	0.254	0.028	0.025
	HI	N	27	27	26	27
		Mean	8.788	8.636	0.091	0.085
		SD	0.084	0.139	0.020	0.025
Post-July2015	Non-HI	N	1,878	1,855	1,838	1,878
		Mean	9.115	8.824	0.092	0.082
		SD	0.291	0.247	0.028	0.024
	HI	N	19	18	19	19
		Mean	8.862	8.775	0.107	0.100
		SD	0.064	0.154	0.022	0.024
Pre-diff (HI tech – non-HI tech)			(0.27)	(0.13)	0.01	0.01
Post-diff (HI tech – non-HI tech)			(0.25)	(0.05)	0.02	0.02
DID of raw means			0.01	0.09	0.01	0.01

Table OA2. LEHD Cross-state Analysis -- Summary Statistics of the Dependent Variables

This table presents the summary statistics of the dependent variables reported. I{4}-I{32} denote indicator variables for the job spell surviving in the 4th-32nd quarter since the job spell started. Log(job-spell) denotes the number of quarters the job lasted in logs. Log(wage4)-Log(wage32) denote quarterly wages at the 4th-32nd quarter since the job spell started. Log(cwage4)-Log(cwage32) denote cumulative wage at the 4th-32nd quarter since the job spell started, in logs. dLog(wage4)-dLog(wage32) denote the logged differences in quarterly wage at the 4th-32nd quarter since the job spell started and the initial wage of the job. Log(cjobs4)-Log(cjob32) denote cumulative number of jobs taken (in logs) in the 4th-32nd quarter of the worker's employment history. Log(cwageE4)-Log(cwageE32) denote the worker's cumulative earnings (in logs) in the 4th-32nd quarter of the worker's employment history. Log(State4)-Log(State32) denote the cumulative number of switches in states, Log(Ind4)-Log(Ind32) denote the cumulative number of switches in industries, and Log(StNoInd4)-Log(StNoInd32) denote the cumulative number of switches in states but not in industries, in the 4th-32nd quarter of the worker's employment history.

Variable	Mean	St.Dev	Variable	Mean	St.Dev	Variable	Mean	St.Dev
I{4}	0.845	0.362	dLog(wage4)	0.049	0.465	Log(State8)	0.027	0.136
I{8}	0.583	0.493	dLog(wage8)	0.076	0.520	Log(State12)	0.033	0.154
I{12}	0.434	0.496	dLog(wage12)	0.101	0.546	Log(State16)	0.040	0.171
I{16}	0.331	0.471	dLog(wage16)	0.128	0.566	Log(State20)	0.048	0.187
I{20}	0.261	0.439	dLog(wage20)	0.151	0.582	Log(State24)	0.055	0.202
I{24}	0.208	0.406	dLog(wage24)	0.169	0.595	Log(State28)	0.062	0.216
I{28}	0.160	0.367	dLog(wage28)	0.191	0.614	Log(State32)	0.070	0.230
I{32}	0.124	0.329	dLog(wage32)	0.211	0.632	Log(Ind4)	0.051	0.186
Log(job-spell)	2.363	0.977	Log(cjobs4)	0.383	0.385	Log(Ind8)	0.106	0.270
Log(wage4)	9.578	0.777	Log(cjobs8)	0.498	0.435	Log(Ind12)	0.152	0.327
Log(wage8)	9.636	0.750	Log(cjobs12)	0.600	0.468	Log(Ind16)	0.195	0.371
Log(wage12)	9.675	0.739	Log(cjobs16)	0.686	0.492	Log(Ind20)	0.234	0.408
Log(wage16)	9.708	0.735	Log(cjobs20)	0.761	0.512	Log(Ind24)	0.270	0.438
Log(wage20)	9.740	0.731	Log(cjobs24)	0.825	0.528	Log(Ind28)	0.304	0.464
Log(wage24)	9.763	0.727	Log(cjobs28)	0.886	0.543	Log(Ind32)	0.340	0.489
Log(wage28)	9.785	0.731	Log(cjobs32)	0.939	0.557	Log(StNoInd4)	0.002	0.034
Log(wage32)	9.804	0.733	Log(cwageE4)	10.887	0.682	Log(StNoInd8)	0.005	0.058
Log(cwage4)	11.003	0.885	Log(cwageE8)	11.631	0.654	Log(StNoInd12)	0.008	0.075
Log(cwage8)	11.765	0.767	Log(cwageE12)	12.054	0.646	Log(StNoInd16)	0.011	0.089
Log(cwage12)	12.204	0.714	Log(cwageE16)	12.353	0.642	Log(StNoInd20)	0.014	0.100
Log(cwage16)	12.514	0.683	Log(cwageE20)	12.586	0.642	Log(StNoInd24)	0.016	0.110
Log(cwage20)	12.762	0.663	Log(cwageE24)	12.778	0.643	Log(StNoInd28)	0.019	0.119
Log(cwage24)	12.966	0.649	Log(cwageE28)	12.942	0.645	Log(StNoInd32)	0.021	0.127
Log(cwage28)	13.137	0.641	Log(cwageE32)	13.083	0.646			
Log(cwage32)	13.290	0.630	Log(State4)	0.017	0.108			

Table OA3. CNCs and High-Tech Workers' Job Duration and Wage: Controlling for Local Labor Market Thickness (LEHD)

This table reports the differential effect of CNC enforceability on job duration and wage across job tenure, by industry (high-tech jobs vs. non-tech jobs), after controlling for total employment in state-three-digit NAICS code-year (in logs). In Panel A, the dependent variables are dummy variables for the job spell surviving at 4^{th}, …, 32^{nd} quarter of the job spell for columns (1)-(8), and the log of length of job spells in number of quarters for column (9). In Panel B, the dependent variables are the log of quarterly wages at 4^{th}, …, 32^{nd} quarter of the job spell. CNC Score is measured as the 2009 CNC enforceability index scores. Estimation samples are all jobs that are not right censored by the quarter for columns (1)-(8) of Panel A, and all jobs that started its spell in year 2000 or earlier for column (9) of Panel A, and all continuing jobs in the quarter for Panel B. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Panel A. Job Duration

Dependent Variable: Job spell survival at	(1) 4th qr	(2) 8th qr	(3) 12th qr	(4) 16th qr	(5) 20th qr	(6) 24th qr	(7) 28th qr	(8) 32th qr	(9) Ln(job-spell)
Tech X CNC Score	-0.0005	0.0029**	0.0037***	0.0044***	0.0049***	0.0056***	0.0045***	0.0051***	0.0146***
	(0.0008)	(0.0011)	(0.0009)	(0.0012)	(0.0010)	(0.0009)	(0.0008)	(0.0007)	(0.0028)
# of observations	12984300	12425700	11971100	11602500	11334900	11127400	10861700	10661700	6492100
R-squared	0.2108	0.1742	0.1732	0.1768	0.1817	0.1836	0.1831	0.1885	0.2113
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs that are not right censored by the quarter								Spell started 2000 or earlier

Panel B. Wage

Dependent Variable: Log of wage at xth quarter	(1) 4th qr	(2) 8th qr	(3) 12th qr	(4) 16th qr	(5) 20th qr	(6) 24th qr	(7) 28th qr	(8) 32th qr
Tech X CNC Score	-0.0057***	-0.0065***	-0.0067***	-0.0068***	-0.0059***	-0.0052***	-0.0058***	-0.0056***
	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0009)	(0.0010)	(0.0013)	(0.0017)
# of observations	10904200	7397200	5399500	4048400	3145300	2478900	1858400	1412600
R-squared	0.6726	0.6090	0.5764	0.5570	0.5429	0.5323	0.5237	0.5114
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]							
Sample	All continuing jobs in the quarter							

Table OA4. CNCs and the Probability of High-Tech Workers' Switching States or Industries at Job Transition (LEHD)

This table reports the differential effect of CNC enforceability on the probability of state switches, industry switches, state switches but not industry switches, and industry switches but not state switches at job transition by industry (high-tech jobs vs. non-tech jobs). The dependent variables are dummy variables for switching states at job transitions in Panel A, dummy variables for three-digit NAICS code switches at job transitions in Panel B, dummy variables for changes in states, but no changes in three-digit NAICS codes at job transitions in Panel C, and dummy variables for changes in three-digit NAICS codes but no changes in states in Panel D, for job transitions occurring at any point in time in job tenure for column (1), and for job transitions occurring at 4th, …, 32nd quarter of job tenure in columns (2) ~ (9). The high-tech job dummy is that of the pre-transition job. CNC Score is measured as the 2009 CNC enforceability index scores of the state in which the pre-transition job is geographically located in. The job-level fixed effects controls for the job characteristics of the pre-transition job. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Panel A. Switch States	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Dummy for switching state at	During job tenure	4th qr	8th qr	12th qr	16th qr	20th qr	24th qr	28th qr	32th qr
Tech X CNC Score	0.0106*	0.0087	0.0103*	0.0126**	0.0088	0.012	0.0122	0.0139*	0.005
	(0.0062)	(0.0076)	(0.0059)	(0.0059)	(0.0067)	(0.0072)	(0.0072)	(0.0069)	(0.0099)
R-squared	0.1194	0.1801	0.2047	0.2615	0.3083	0.3605	0.4086	0.4609	0.5054
Panel B. Switch Industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Dummy for switching industry at	During job tenure	4th qr	8th qr	12th qr	16th qr	20th qr	24th qr	28th qr	32th qr
Tech X CNC Score	0.0027	0.0018	0.0006	0.0046	0.0006	0.0062	0.0036	0.0089**	-0.0043
	(0.0029)	(0.0028)	(0.0028)	(0.0028)	(0.0037)	(0.0038)	(0.0046)	(0.0033)	(0.0061)
R-squared	0.1126	0.203	0.1901	0.242	0.2808	0.3423	0.3833	0.4379	0.4729
# of observations	12320000	4349000	2983000	1686000	1029000	679000	491000	345000	238000
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs in transition	All jobs in transitions in the quarter							

Panel C. Switch State but not Industry Dependent Variable: Dummy for switching state but not industry at	(1) During job tenure	(2) 4th qr	(3) 8th qr	(4) 12th qr	(5) 16th qr	(6) 20th qr	(7) 24th qr	(8) 28th qr	(9) 32th qr
Tech X CNC Score	0.0016***	0.0014**	0.0021***	0.0021***	0.0014***	0.0014***	0.0013***	0.0007**	0.0008
	(0.0004)	(0.0006)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
R-squared	0.0486	0.096	0.1174	0.1603	0.2022	0.2524	0.2872	0.3324	0.3769
Panel D. Switch Industry but not State Dependent Variable: Dummy for switching industry but not state at	(1) During job tenure	(2) 4th qr	(3) 8th qr	(4) 12th qr	(5) 16th qr	(6) 20th qr	(7) 24th qr	(8) 28th qr	(9) 32th qr
Tech X CNC Score	-0.0063*	-0.0055	-0.0076**	-0.0059	-0.0068*	-0.0044	-0.0073**	-0.0043	-0.0085**
	(0.0034)	(0.0045)	(0.0031)	(0.0035)	(0.0034)	(0.0039)	(0.0035)	(0.0047)	(0.0040)
R-squared	0.0992	0.1692	0.1745	0.2235	0.2732	0.3328	0.3713	0.4223	0.4590
# of observations	12320000	4349000	2983000	1686000	1029000	679000	491000	345000	238000
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs in transition	All jobs in transitions in the quarter							

Table OA5. CNCs and High-Tech Workers' Unemployment Spell (LEHD)

This table reports the differential effect of CNC enforceability on the length of unemployment spell by industry (high-tech jobs vs. non-tech jobs). Unemployment is defined by the missing spell between two non-continuous job spells. The dependent variable is the log of length of unemployment spells in number of quarters. The high-tech job dummy is that of the pre-unemployment job. CNC Score is measured as the 2009 CNC enforceability index scores of the pre-unemployment job. The job-level fixed effects controls for the job characteristics of the pre-unemployment job. Estimation sample consists of all spells between non-continuous job spells. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)
Dependent Variable	Ln(unemployment-spell)
Tech X CNC Score	-0.0051
	(0.0033)
# of observations	4540000
R-squared	0.1241
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]
Sample	All spells between non-continuous job spells

Table OA6. CNCs (in Ranks) and High-Tech Workers' Job Duration and Wage across Job Tenure (LEHD)

This table reports the differential effect of CNC enforceability on job duration by industry (high-tech jobs vs. non-tech jobs) in Panel A, and on wage across job tenure by industry in Panel B. The dependent variables are dummy variables for the job spell surviving at 4th, 8th, …, 32nd quarter of the job spell for column (1) ~ (8) of Panel A, and the log of length of job spells in number of quarters for column (9) of Panel A, the log of quarterly wages at 4th, 8th, …, 32nd quarter of the job spell for Panel B. CNC Rank is measured as the ranks of the 2009 CNC enforceability index scores. Estimation samples are all jobs that are not right censored by the quarter for columns (1) ~ (8) of Panel A, all jobs that started its spell in year 2000 or earlier for column (9) of Panel A, and all continuing jobs in the quarter for Panel B. All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Panel A. Job Duration

Dependent Variable: Job spell survival at	(1) 4th qr	(2) 8th qr	(3) 12th qr	(4) 16th qr	(5) 20th qr	(6) 24th qr	(7) 28th qr	(8) 32th qr	(9) Ln(job-spell)
Tech X CNC Rank	0.0004	0.0052**	0.0065***	0.0060**	0.0073***	0.0085***	0.0064***	0.0072***	0.0224***
	(0.0012)	(0.0021)	(0.0021)	(0.0028)	(0.0024)	(0.0021)	(0.0023)	(0.0021)	(0.0063)
# of observations	12984300	12425700	11971100	11602500	11334900	11127400	10861700	10661700	6492100
R-squared	0.2108	0.1741	0.1731	0.1767	0.1817	0.1835	0.1831	0.1884	0.2112
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs that are not right censored by the quarter								Spell started 2000 or earlier

Panel B. Wage

Dependent Variable Log of wage at xth quarter	(1) 4th qr	(2) 8th qr	(3) 12th qr	(4) 16th qr	(5) 20th qr	(6) 24th qr	(7) 28th qr	(8) 32th qr
Tech X CNC Rank	-0.0085***	-0.0087***	-0.0101***	-0.0101***	-0.0097***	-0.0092***	-0.0103***	-0.0113***
	(0.0015)	(0.0027)	(0.0024)	(0.0021)	(0.0020)	(0.0018)	(0.0026)	(0.0032)
# of observations	10904200	7397200	5399500	4048400	3145300	2478900	1858400	1412600
R-squared	0.6726	0.6089	0.5764	0.5570	0.5429	0.5323	0.5237	0.5114
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]							
Sample	All continuing jobs in the quarter							

Table OA7. CNCs (in Ranks) and Job Duration and Wage across Job Tenure: Sub-Samples by Industry and Initial Wage (LEHD)

This table reports the differential effect of CNC enforceability on job duration and wage throughout job tenure, across sub-samples by industry (high-tech jobs vs non-tech jobs) and initial wage (high-initial-wage jobs vs low-initial-wage jobs). High–initial-wage jobs are jobs whose starting wage is above the 98th percentile in the distribution of starting wages of jobs that have the same three-digit NAICS codes. The dependent variables are dummy variables for the job spell surviving at 4^{th}, 12^{th}, 20^{th}, 28^{th} quarter of the job spell for columns (1)-(4), and the log of length of job spells in number of quarters for column (5), the log of quarterly wages at 4^{th}, 12^{th}, 20^{th}, 28^{th} quarter of the job spell for columns (6) ~ (9). CNC Rank is measured as the ranks of the 2009 CNC enforceability index scores. Estimation samples are all jobs that are not right censored by the quarter for columns (1) ~ (4), all jobs that started its spell in year 2000 or earlier for column (5), and all continuing jobs in the quarter for columns (6) ~ (9). All standard errors are clustered by state. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent Variable	Job spell survival at					Log of wage at			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	4th qr	12th qr	20th qr	28th qr	Ln(job-spell)	4th qr	12th qr	20th qr	28th qr
Tech X High-initial-wage X CNC Rank (β_1)	0.0087***	0.0210***	0.0183***	0.0139***	0.0425***	-0.0181**	-0.0227**	-0.0287***	-0.0350***
	(0.0014)	(0.0067)	(0.0043)	(0.0038)	(0.0078)	(0.0076)	(0.0086)	(0.0072)	(0.0074)
Tech X CNC Rank (β_2)	0.0002	0.0061***	0.0070***	0.0062**	0.0216***	-0.0081***	-0.0096***	-0.0091***	-0.0095***
	(0.0012)	(0.0021)	(0.0024)	(0.0023)	(0.0063)	(0.0014)	(0.0024)	(0.0019)	(0.0026)
High-initial-wage X CNC Rank (β_3)	0.0014	-0.0118*	-0.0086**	-0.0073***	-0.0150**	-0.0314***	-0.0322***	-0.0431***	-0.0426***
	(0.0016)	(0.0059)	(0.0035)	(0.0018)	(0.0057)	(0.0074)	(0.0096)	(0.0130)	(0.0140)
# of observations	12984300	11971100	11334900	10861700	6492100	10904200	5399500	3145300	1858400
R-squared	0.2108	0.1732	0.1817	0.1831	0.2112	0.6726	0.5764	0.5430	0.5238
High vs Low Wage in Tech industry ($\beta_1+\beta_3$)	0.0100***	0.0093***	0.0097***	0.00658**	0.0274***	-0.0495***	-0.0549***	-0.0717***	-0.0777***
p value	6.46e-09	0.000197	0.00157	0.0384	0.000151	0.000925	0.00289	3.76e-06	1.27e-07
Tech vs Non-Tech in High-initial-wage jobs ($\beta_1+\beta_2$)	0.0088***	0.0271***	0.0253***	0.0201***	0.0640***	-0.0262***	-0.0323***	-0.0377***	-0.0446***
p value	4.00e-06	0.000998	9.09e-06	5.00e-05	2.95e-07	0.00288	0.000592	0.000112	1.16e-05
Fixed Effects	State + [Industry - Starting Year - Firm Size - Starting Wage - Starting Age - Sex]								
Sample	All jobs that are not right censored by the quarter				Spell started 2000 or earlier	All continuing jobs in the quarter			

Table OA8: Industry Codes Corresponding to "Technology Business" Used in Analysis of the Hawaii Natural Experiment
US Census codes for the CPS analysis utilizes the bridge to the NAICS codes provided by the Census.

NAICS 4-digit codes for QWI analysis	Census Classification codes for CPS analysis
3341 Computer and Peripheral Equipment Manufacturing	3365 Computer and peripheral equipment manufacturing
3342 Communications Equipment Manufacturing	3370 Communications, audio, and video equipment manufacturing
3343 Audio and Video Equipment Manufacturing	3390 Electronic component and product manufacturing, n.e.c.
3344 Semiconductor and Other Electronic Component Manufacturing	6490 Software publishing
5112 Software Publishers	6695 Data processing, hosting, and related services
5182 Data Processing, Hosting, and Related Services	7380 Computer systems design and related services

Table OA9: QWI Mobility and Wage Analysis for Hawaii – Triple Difference Results including control for employment

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses are clustered at the state level. All specifications are the same as in Table 9 except that an additional control variable -- Log Beginning-of-Quarter Employment (i.e., Log Emp) is included as a control. Data is from the QWI, 2013Q2 to 2017Q2. "Tech" is defined as QWI 4-digit industry classifications that cover software design, development and services, to concord with the definition of "technology business" in the Hawaii statute. In Panel A, the dependent variable in Cols 1 to 4 is the Overall Separation Rate defined as All Separations (i.e., Sep) divided by Employment in the Reference Quarter (i.e., EmpTotal), and in Cols 5 to 8 is the Beginning-of-Quarter separation rate (i.e., SepBegR).In Panel B, the dependent variable in Cols 1 to 4 is the log of overall Average Monthly Earnings (Full Quarter Employment) (i.e., log EarnS), and in Cols 5 to 8 is the log of the Average Monthly Earnings of All Hires into Full Quarter Employment (i.e., log EarnHirAS)."Post" is defined as July 2015 and afterwards; SR_Post is 2015Q3 to 2016Q2, and LR_Post is 2016Q3 to 2017Q2. Cols 1-2 and 5-6 are limited to the 40 states closest to Hawaii in the CNC score in absolute terms, while other columns include all states. All specifications use Beginning-of-quarter Employment (Emp) as (analytical) weights. Number of observations adjusts for weights and singleton cells, i.e., drops zero weights and singleton-cells (when fixed effects are added). The mean (sd) of the Overall Separation Rate for Tech industries in the pre-July 2015 period is 0.091 (0.020) and for Beginning-of-Quarter Separation Rate is 0.085 (0.025).The mean (sd) for Tech industries in the pre-July 2015 of Log Overall Average Monthly Earnings period is 8.788 (0.084) and of Log Hires Average Monthly Earnings is 8.640 (0.140).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: QWI Mobility Variables	Overall Separation Rate				Beginning-of-Quarter Separation Rate			
Post X HI X Tech	0.0167***		0.0176***		0.0188***		0.0202***	
	(0.00161)		(0.00121)		(0.00131)		(0.00117)	
SR_Post X HI X Tech		0.0158***		0.0170***		0.0189***		0.0203***
		(0.00154)		(0.00122)		(0.00105)		(0.00108)
LR_Post X HI X Tech		0.0184***		0.0190***		0.0188***		0.0200***
		(0.00210)		(0.00157)		(0.00228)		(0.00193)
Observations	163,965	163,965	205,608	205,608	166,450	166,450	208,632	208,632
R-squared	0.948	0.945	0.949	0.945	0.909	0.902	0.908	0.899
Panel B: QWI Wage Variables	Log Overall Average Monthly Earnings				Log Hires Average Monthly Earnings			
Post X HI X Tech	0.00964***		0.00712**		0.0441***		0.0424***	
	(0.00282)		(0.00270)		(0.00457)		(0.00361)	
SR_Post X HI X Tech		0.0121***		0.0100***		0.0558***		0.0548***
		(0.00276)		(0.00238)		(0.00479)		(0.00352)
LR_Post X HI X Tech		0.00451		0.00104		0.0198***		0.0166***
		(0.00653)		(0.00546)		(0.00625)		(0.00593)
Observations	166,529	166,529	208,728	208,728	164,140	164,140	205,828	205,828
R-squared	0.992	0.992	0.993	0.993	0.975	0.975	0.975	0.975
Sample	40 States	40 States	All	All	40 States	40 States	All	All
Control for Log Beginning-of-Quarter Employment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind X Year-Qtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Ind	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Year-Qtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table OA10: "Technology Employers" (Table 1 in Paytas and Berglund, 2004)

NAICS 4	NAICS 6	NAICS industry
2111	211100	Oil and Gas Extraction
2111	211111	Crude Petroleum and Natural Gas Extraction
3251	325100	Basic Chemical Manufacturing
3251	325110	Petrochemical Manufacturing
3251	325120	Industrial Gas Manufacturing
3251	325131	Inorganic Dye and Pigment Manufacturing
3251	325182	Carbon Black Manufacturing
3251	325188	All Other Basic Inorganic Chemical Manufacturing
3251	325192	Cyclic Crude and Intermediate Manufacturing
3251	325199	All Other Basic Organic Chemical Manufacturing
3254	325400	Pharmaceutical and Medicine Manufacturing
3254	325411	Medicinal and Botanical Manufacturing
3254	325412	Pharmaceutical Preparation Manufacturing
3254	325413	In-Vitro Diagnostic Substance Manufacturing
3254	325414	Biological Product (except Diagnostic) Manufacturing
3332	333200	Industrial Machinery Manufacturing
3332	333210	Sawmill and Woodworking Machinery Manufacturing
3332	333220	Plastics and Rubber Industry Machinery Manufacturing
3332	333292	Textile Machinery Manufacturing
3332	333293	Printing Machinery and Equipment Manufacturing
3332	333294	Food Product Machinery Manufacturing
3332	333295	Semiconductor Machinery Manufacturing
3332	333298	All Other Industrial Machinery Manufacturing
3333	333300	Commercial and Service Industry Machinery Manufacturing
3333	333313	Office Machinery Manufacturing
3333	333314	Optical Instrument and Lens Manufacturing
3333	333315	Photographic and Photocopying Equipment Manufacturing
3333	333319	Other Commercial and Service Industry Machinery Manufacturing
3341	334100	Computer and Peripheral Equipment Manufacturing
3341	334111	Electronic Computer Manufacturing

NAICS 4	NAICS 6	NAICS industry
3341	334113	Computer Terminal Manufacturing
3341	334119	Other Computer Peripheral Equipment Manufacturing
3342	334200	Communications Equipment Manufacturing
3342	334210	Telephone Apparatus Manufacturing
3342	334220	Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing
3342	334290	Other Communications Equipment Manufacturing
3343	334300	Audio and Video Equipment Manufacturing
3343	334310	Audio and Video Equipment Manufacturing
3344	334400	Semiconductor and Other Electronic Component Manufacturing
3344	334412	Bare Printed Circuit Board Manufacturing
3344	334413	Semiconductor and Related Device Manufacturing
3344	334414	Electronic Capacitor Manufacturing
3344	334415	Electronic Resistor Manufacturing
3344	334417	Electronic Connector Manufacturing
3344	334418	Printed Circuit Assembly (Electronic Assembly) Manufacturing
3344	334419	Other Electronic Component Manufacturing
3345	334500	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3345	334510	Electromedical and Electrotherapeutic Apparatus Manufacturing
3345	334511	Search, Detection, Navigation, Guidance, Aeronautical, and Nautical System and Nautical System and Instrument Manufacturing
3345	334512	Automatic Environmental Control Manufacturing for Residential, Commercial, and Appliance Use
3345	334513	Instruments and Related Products Manufacturing for Measuring, Displaying, and Controlling industrial Process Variables
3345	334514	Totalizing Fluid Meter and Counting Device Manufacturing
3345	334515	Instrument Manufacturing for Measuring and Testing Electricity and Electrical Signals
3345	334516	Analytical Laboratory Instrument Manufacturing
3345	334517	Irradiation Apparatus Manufacturing
3345	334519	Other Measuring and Controlling Device Manufacturing
3364	336400	Aerospace Product and Parts Manufacturing
3364	336411	Aircraft Manufacturing
3364	336412	Aircraft Engine and Engine Parts Manufacturing
3364	336413	Other Aircraft Part and Auxiliary Equipment Manufacturing

NAICS 4	NAICS 6	NAICS industry
3364	336419	Other Guided Missile and Space Vehicle Parts and Auxiliary Equipment Manufacturing
4234	423400	Professional and Commercial Equipment and Supplies Merchant Wholesalers
5112	511200	Software Publishers
5112	511210	Software Publishers
5161	516100	Internet Publishing and Broadcasting
5179	517900	Other Telecommunications
5181	518100	Internet Service Providers and Web Search Portals
5181	518111	Internet Service Providers
5182	518200	Data Processing, Hosting, and Related Services
5413	541300	Architectural, Engineering, and Related Services
5413	541310	Architectural Services
5413	541330	Engineering Services
5413	541370	Surveying and Mapping (except Geophysical) Services
5413	541380	Testing Laboratories
5415	541500	Computer Systems Design and Related Services
5415	541511	Custom Computer Programming Services
5415	541512	Computer Systems Design Services
5416	541600	Management, Scientific, and Technical Consulting Services
5417	541700	Scientific Research and Development Services
5417	541710	Research and Development in the Physical, Engineering, and Life Sciences
5417	541720	Research and Development in the Social Sciences and Humanities

Table OA11a: Summary statistics on workforce characteristics by Tech Sector and Enforceability -- 1991-2008 period using public QWI data

This table presents summary statistics on workforce characteristics constructed using 3-digit NAICS by state by year by quarter data from the public QWI, which in turn uses the LEHD (Version 4.4) data. Panel A uses data on all states, and Panel B uses the 30 states in our LEHD sample, for years 1991 to 2008. Note that for the LEHD analysis in the paper, we restricted the sample to workers earning more than $35,000, so the underlying sample here even in Panel B is different from our analysis sample. "Log (Earnings)" is Log (EarnS) where EarnS is defined as the average monthly earnings of employees with stable jobs (*i.e.*, worked with the same firm throughout the quarter). "Beginning of Period Separation Rate" is defined as SepBeg (the estimated number of workers whose job in the previous quarter continued and ended in the given quarter) as a percent of average employment. "Fraction Male" is the industry-state-year quarter fraction of beginning-of-quarter employment (Emp) who are male. "Fraction Age <35" is the industry-state-year quarter fraction of beginning-of-quarter employment (Emp) who are aged less than 35 years. "Fraction in Large Firms" is the industry-state-year quarter fraction of beginning-of-quarter employment (Emp) who are employed in firms with more than 249 employees. The reported average means and standard deviations (provided in parenthesis) are weighted, with state-industry-quarter Beginning of Quarter Employment (Emp) as (analytical) weights. Emp is defined specifically as the estimate of the total number of jobs on the first day of the reference quarter. The states in each of the enforceability categories is listed in Appendix Table 2b in the text.

	Log Earnings		Beginning of Period Separation Rate		Fraction Male		Fraction Age <35		Fraction in Large Firms	
	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech
Panel A: Full sample										
Bottom Quintile (Low Enforceability)	7.88	8.54	0.152	0.096	0.520	0.603	0.421	0.358	0.493	0.537
	(0.51)	(0.27)	(0.07)	(0.03)	(0.19)	(0.09)	(0.11)	(0.07)	(0.24)	(0.18)
Middle 60% (Moderate Enforceability)	7.80	8.40	0.156	0.088	0.509	0.628	0.422	0.333	0.531	0.587
	(0.45)	(0.25)	(0.08)	(0.03)	(0.22)	(0.11)	(0.12)	(0.07)	(0.24)	(0.21)
Top quintile (High enforceability)	7.86	8.41	0.151	0.090	0.506	0.608	0.408	0.335	0.538	0.564
	(0.47)	(0.24)	(0.07)	(0.03)	(0.20)	(0.11)	(0.11)	(0.07)	(0.24)	(0.20)
Panel B: LEHD (30 states) sample										
Bottom Quintile (Low Enforceability)	7.83	8.52	0.157	0.096	0.525	0.609	0.430	0.358	0.488	0.538
	(0.48)	(0.28)	(0.08)	(0.03)	(0.19)	(0.09)	(0.11)	(0.07)	(0.24)	(0.18)
Middle 60% (Moderate Enforceability)	7.78	8.39	0.162	0.091	0.514	0.625	0.429	0.342	0.530	0.591
	(0.45)	(0.28)	(0.08)	(0.03)	(0.21)	(0.11)	(0.12)	(0.07)	(0.24)	(0.21)
Top quintile (High enforceability)	7.88	8.43	0.151	0.093	0.509	0.600	0.404	0.340	0.548	0.550
	(0.45)	(0.23)	(0.07)	(0.03)	(0.20)	(0.10)	(0.11)	(0.07)	(0.24)	(0.18)

Table OA11b: Tech share of Employment and patent count (average over 2000-2004 period) using public QWI data

This table provides the average annual patent count and total employment for Tech and Non-Tech sectors, per the definition of Tech sector used in our LEHD analysis. The total employment was constructed for the US as a whole (not just the 30 LEHD states, as patent data is for the whole country) by using data (for the third quarter for each of the 2000-2004 years) from the Quarterly Workforce Indicators (QWI) data, and the patent count data is from Goldschlag, Lybbert and Zolas (2019). In addition to the difference from number of states, note that for the LEHD analysis we restrict the sample to workers earning more than $35,000, so the relative shares of workers are likely to be different in the LEHD sample than in the full sample presented here using publicly available QWI data.

	Average annual patent count	Average annual total Employment (in 000s)	Patent share	Employment share
Non-Tech	62,457	98,400	37.9%	85.4%
Tech	102,317	16,760	62.1%	14.5%
Total	164,773	115,200	100.0%	100.0%

Table OA12: Ranks and Raw scores underlying CNC Enforceability Index for 2009

State	Rank per Starr (2019) Measure	Rank per Bishara (2011) measure	Starr Measure	Bishara Measure(Stdzd)	Statute of enforce-ability	Protectable interest	Plaintiff's burden of proof	Considerati on at inception	Considerati on post-inception	Overbroad contracts	Quit vs. Fire
					Q1	Q2	Q3	Q3a	Q3b & 3c	Q4	Q8
Alaska	4	4	-0.98	-0.97	5	4.0	1.0	10.0	4.6	3.0	4.6
Alabama	29	21	0.36	0.06	3	8.0	3.0	10.0	10.0	8.0	7.0
Arkansas	8	3	-0.58	-0.99	5	6.0	4.0	10.0	10.0	0.0	0.0
Arizona	24	20	0.15	0.02	5	7.0	8.0	6.4	10.0	2.0	6.4
California	2	2	-3.79	-3.76	1	1.0	1.0	0.6	0.6	0.0	0.0
Colorado	30	36	0.38	0.54	6	6.0	7.0	10.0	5.0	5.0	8.0
Connecticut	50	49	1.26	1.09	5	9.0	7.0	10.0	10.0	6.0	10.0
District of Columbia	21	11	0.12	-0.38	5	9.0	7.0	10.0	7.0	4.0	1.0
Delaware	36	38	0.52	0.61	5	6.0	6.0	10.0	8.0	3.0	10.0
Florida	51	51	1.60	1.43	10	10.0	8.0	10.0	10.0	7.0	6.0
Georgia	17	12	0.02	-0.34	3	7.0	5.0	10.0	10.0	0.0	6.0
Hawaii	13	19	-0.17	-0.02	8	6.0	5.0	6.3	6.0	6.3	6.3
Iowa	46	44	1.01	0.95	5	8.0	8.0	10.0	9.0	9.0	7.0
Idaho	41	41	0.77	0.69	5	9.0	7.0	7.0	7.7	8.0	10.0
Illinois	44	45	0.95	1.00	5	7.0	6.0	10.0	10.0	9.0	9.0
Indiana	39	39	0.70	0.62	5	7.0	6.0	10.0	10.0	3.0	9.0
Kansas	49	50	1.21	1.21	5	8.0	7.0	10.0	10.0	10.0	9.0
Kentucky	42	43	0.85	0.94	5	7.0	9.0	9.0	9.0	9.0	7.0
Louisiana	35	40	0.50	0.67	8	6.0	7.0	7.0	10.0	4.0	8.0
Massachusetts	34	32	0.48	0.49	5	7.0	7.0	10.0	6.0	7.0	7.0
Maryland	37	34	0.60	0.51	5	7.0	6.0	10.0	10.0	7.3	6.0
Maine	31	30	0.41	0.48	5	6.0	6.0	10.0	8.0	7.0	7.0
Michigan	33	37	0.46	0.56	5	6.0	6.0	10.0	8.0	8.0	7.2
Minnesota	16	15	-0.07	-0.15	5	7.0	4.0	10.0	4.0	7.0	6.0
Missouri	48	46	1.08	1.02	8	8.0	7.0	10.0	10.0	7.0	6.0

State	Rank per Starr (2019) Measure	Rank per Bishara (2011) measure	Starr Measure	Bishara Measure(Stdzd)	Statute of enforce-ability	Protectable interest	Plaintiff's burden of proof	Considerati on at inception	Considerati on post-inception	Overbroad contracts	Quit vs. Fire
Mississippi	19	16	0.04	-0.14	5	8.0	6.0	8.0	6.0	9.0	4.0
Montana	7	7	-0.65	-0.71	2	5.0	4.0	10.0	5.0	5.2	5.2
North Carolina	25	24	0.18	0.11	4	7.0	6.0	10.0	5.0	4.0	8.0
North Dakota	1	1	-4.23	-4.14	0	0.0	0.0	0.0	0.0	0.0	0.0
Nebraska	14	9	-0.13	-0.51	5	7.0	2.0	10.0	10.0	0.0	5.7
New Hampshire	27	27	0.26	0.33	5	6.0	6.0	9.0	8.0	7.0	6.8
New Jersey	43	42	0.90	0.82	5	8.0	6.0	10.0	9.0	9.0	8.0
New Mexico	40	28	0.74	0.41	5	10.0	6.0	9.0	7.0	7.4	7.4
Nevada	18	23	0.03	0.10	4	6.0	7.0	8.0	7.0	7.0	6.5
New York	3	5	-1.15	-0.95	5	4.0	4.0	3.0	8.0	9.0	4.0
Ohio	20	29	0.08	0.44	5	3.0	3.0	10.0	10.0	7.0	9.0
Oklahoma	5	7	-0.94	-0.71	2	3.0	6.0	8.0	5.0	6.0	5.0
Oregon	22	26	0.14	0.24	4	6.0	6.0	10.0	5.0	9.0	6.7
Pennsylvania	23	24	0.14	0.11	5	7.0	4.0	10.0	5.0	8.0	7.0
Rhode Island	9	17	-0.33	-0.11	5	5.0	8.0	6.0	6.0	6.0	6.0
South Carolina	12	14	-0.27	-0.24	5	5.0	3.0	10.0	7.0	5.0	6.0
South Dakota	47	47	1.02	1.07	8	7.0	8.0	10.0	10.0	6.0	6.0
Tennessee	32	33	0.45	0.50	4	6.0	6.0	10.0	9.0	8.0	7.2
Texas	11	13	-0.28	-0.26	8	8.0	7.0	4.0	3.0	6.0	6.0
Utah	45	47	1.00	1.07	5	7.0	6.0	10.0	10.0	8.0	10.0
Virginia	10	10	-0.29	-0.45	5	8.0	4.0	7.0	3.0	1.0	10.0
Vermont	37	34	0.60	0.51	5	7.0	6.0	10.0	10.0	7.3	6.0
Washington	28	30	0.34	0.48	5	6.0	6.0	10.0	6.0	9.0	7.0
Wisconsin	15	18	-0.09	-0.08	8	7.0	6.0	10.0	0.0	0.0	7.0
West Virginia	6	6	-0.80	-0.84	2	6.0	6.0	7.0	3.0	7.0	5.2
Wyoming	26	21	0.23	0.06	5	8.0	5.0	10.0	5.0	7.0	6.0

Table OA13: Correlation of CNC enforceability Index with State-Level Variables

See Figure OA8 for scatter plot versions of these regressions. Dependent variable is the CNC enforceability index for 2009 from Starr (2019). State GDP per capita is in year 2000 USD and is for based on BEA data. Top corporate state tax rate is for year 2000.Union membership density for 2000 is from http://www.unionstats.com. Right to Work is a dummy variable for states that passed right to work (anti-union) legislation as at year 2000. Implied contract exception, public policy exception and good faith exception are dummy variables for these three exceptions to the employment-at-will doctrine, for year 1999, taken from Autor, Donohue and Schwab (2006). ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log real GDP per capita	0.501	0.501							0.789
	(0.837)	(0.837)							(1.025)
Top state corporate tax rate			-0.0724						-0.0889
			(0.0485)						(0.0543)
Union density				-0.0149					-0.0181
				(0.0264)					(0.0429)
Right to work dummy					0.0677				-0.194
					(0.302)				(0.460)
Implied contract exception dummy						-0.410			-0.654
						(0.384)			(0.625)
Public policy exception dummy							-0.234		0.178
							(0.371)		(0.573)
Good faith exception dummy								-0.293	-0.434
								(0.357)	(0.411)
Constant	-5.133	-5.133	0.563	0.312	0.0663	0.431	0.282	0.159	-6.726
	(8.727)	(8.727)	(0.346)	(0.411)	(0.196)	(0.347)	(0.332)	(0.168)	(10.60)
Observations	50	50	50	50	50	50	50	50	50
R-squared	0.007	0.007	0.044	0.007	0.001	0.023	0.008	0.014	0.122

Appendix G. Data Replication Appendix

To replicate our analyses using the QWI data, download the data at https://ledextract.ces.census.gov/static/data.html for the time period 2013Q2 to 2017Q1.

Stata 16 was then used to run the following setup program, followed by the table and figure creation program. Those programs are pasted in their entirety below. Note that the relevant directories will need to be updated in order for the programs to run.

```
***PROGRAM 1: Data_Setup.do***


*cd \workingdirectory\ /**<- Change this to the directory of the raw data file **/

/**/
insheet using "All_State_QWI_Data_2011_2017.csv", clear
label data "version: QWISE_F MT 30 1993:1-2017:1 V4.1.3 R2017Q4 qwipu_mt_20171116_1120"
drop version
compress
save QWI_raw, replace
**/
use QWI_raw, clear
/** geography labels are from LED documentation here:
https://lehd.ces.census.gov/data/schema/latest/label_fipsnum.csv
**/
label drop _all

label define geography 1 "Alabama"
label define geography 2 "Alaska", add
label define geography 4 "Arizona", add
label define geography 5 "Arkansas", add
label define geography 6 "California", add
label define geography 8 "Colorado", add
label define geography 9 "Connecticut", add
label define geography 10 "Delaware", add
label define geography 11 "District of Columbia", add
label define geography 12 "Florida", add
label define geography 13 "Georgia", add
label define geography 15 "Hawaii", add
label define geography 16 "Idaho", add
label define geography 17 "Illinois", add
label define geography 18 "Indiana", add
label define geography 19 "Iowa", add
label define geography 20 "Kansas", add
label define geography 21 "Kentucky", add
label define geography 22 "Louisiana", add
label define geography 23 "Maine", add
label define geography 24 "Maryland", add
label define geography 25 "Massachusetts", add
label define geography 26 "Michigan", add
label define geography 27 "Minnesota", add
label define geography 28 "Mississippi", add
label define geography 29 "Missouri", add
label define geography 30 "Montana", add
```

```
label define geography 31 "Nebraska", add
label define geography 32 "Nevada", add
label define geography 33 "New Hampshire", add
label define geography 34 "New Jersey", add
label define geography  35 "New Mexico", add
label define geography 36 "New York", add
label define geography 37 "North Carolina", add
label define geography 38 "North Dakota", add
label define geography 39 "Ohio", add
label define geography 40 "Oklahoma", add
label define geography 41 "Oregon", add
label define geography 42 "Pennsylvania", add
label define geography 44 "Rhode Island", add
label define geography 45 "South Carolina", add
label define geography 46 "South Dakota", add
label define geography 47 "Tennessee", add
label define geography 48 "Texas", add
label define geography 49 "Utah", add
label define geography 50 "Vermont", add
label define geography 51 "Virginia", add
label define geography 53 "Washington", add
label define geography 54 "West Virginia", add
label define geography 55 "Wisconsin", add
label define geography 56 "Wyoming", add
label values geography geography


/* Labels from https://lehd.ces.census.gov/data/schema/latest/label_education.csv */
egen edcode=group(education)
replace edcode=edcode-1
label define education 0 "All Education Categories"
label define education 1 "Less than high school", add
label define education 2 "High school or equivalent, no college", add
label define education 3 "Some college or Associate degree", add
label define education 4 "Bachelor's degree or advanced degree", add
label define education 5 "Educational attainment not available (workers aged 24 or younger)", add
label values edcode education


label define flag -2 "no data available in this category for this quarter"
label define flag -1 "data not available to compute this estimate", add
label define flag 1 "OK", add
label define flag 5 "Value suppressed because it does not meet US Census Bureau publication standards.",
add
label define flag 6 "Value calculated from other released measures - no significant distortion", add
label define flag 7 "Value calculated from other released measures - some of which have significantly
distorted data", add
label define flag 9 "Data significantly distorted - fuzzed value released", add
label define flag 10 "Aggregate of cells - no significant distortion", add
label define flag 11 "Aggregate of cells not released because component cells do not meet U.S. Census
Bureau publication standards", add
label define flag 12 "Aggregate of cells - some of which have significantly distorted data", add

label define gender 0 "All Sexes"
label define gender 1 "Male", add
label define gender 2 "Female", add
```

```
label values sex gender

gen agecode=substr(agegrp, 3, 1)
destring agecode, replace
label define agel 0 "All Ages (14-99)"
label define agel 1 "14-18", add
label define agel 2 "19-21", add
label define agel 3 "22-24", add
label define agel 4 "25-34", add
label define agel 5 "35-44", add
label define agel 6 "45-54", add
label define agel 7 "55-64", add
label define agel 8 "65-99", add
label values agecode agel


label define fage 0 "All Firm Ages"
label define fage 1 "0-1 Years", add
label define fage 2 "2-3 Years", add
label define fage 3 "4-5 Years", add
label define fage 4 "6-10 Years", add
label define fage 5 "11+ Years", add
*label define fage N "Firm Age Not Available For Public-Sector Firms", add
label values firmage fage
tab firmage

label define fsize 0 "All Firm Sizes"
label define fsize 1 "0-19 Employees", add
label define fsize 2 "20-49 Employees", add
label define fsize 3 "50-249 Employees", add
label define fsize 4 "250-499 Employees", add
label define fsize 5 "500+ Employees", add
*label define fsize N "Firm Size Not Available For Public-Sector Firms", add
label values firmsize fsize


gen ocode=substr(ownercode,3,1)
destring ocode, replace
label define ownl  0 "State and local government plus private ownership"
label define ownl  1 "Federal government", add
label define ownl  5 "All Private", add
label values ocode ownl

gen ethcode=substr(ethnicity,2,1)
destring ethcode, replace
label define ethcode 0 "All Ethnicities"
label define ethcode 1 "Not Hispanic or Latino", add
label define ethcode 2 "Hispanic or Latino", add
label values ethcode ethcode

label define qtr 1 "1st Quarter of the Year (January-March)"
label define qtr 2 "2nd Quarter of the Year (April-June)", add
label define qtr 3 "3rd Quarter of the Year (July-September)", add
label define qtr 4 "4th Quarter of the Year (October-December)", add
label values quarter qtr
```

```
gen racecode=substr(race,2,1)
destring racecode, replace
label define rcode 0 "All Races"
label define rcode 1 "White Alone", add
label define rcode 2 "Black or African American Alone", add
label define rcode 3 "American Indian or Alaska Native Alone", add
label define rcode 4 "Asian Alone", add
label define rcode 5 "Native Hawaiian or Other Pacific Islander Alone", add
label define rcode 6 "Some Other Race Alone (Not Used)", add
label define rcode 7 "Two or More Race Groups", add
label values racecode rcode

label var year "Year"
label var sex "Sex (0=Both genders)"
label var agegrp "Age groups (A00=All)"
label var agecode "Age groups, Numeric "
label var firmage "Firm Age groups (0=All)"
label var firmsize "Firm Size groups (0=All)"
label var ownercode "Ownercode (A00=All)"
label var ocode "Ownercode, Numeric"
label var ethnicity "Ethnicity (A0=All)"
label var periodicity "A=Annual data, Q=Quarterly data"
label var quarter "Quarter"
label var race "Race (A0=All)"
label var ind_level "Industry Level (4=NAICS Industry Groups)"
label var geo_level "Geographic Level (S=States)"
label var industry "4-digit NAICS Code"
label var education "Education groups (0=All)"
label var geography "Statecodes"

gen statecode=geography
label var statecode "State code (=geography)"

label var season "Seasonally adjusted (U=Unadjusted)"
label var emp "Beginning-of-Quarter Employment"
label var empend "End-of-Quarter Employment"
label var emps "Full-Quarter Employment (Stable)"
label var empspv "Full-Quarter Employment in the Previous Quarter"
label var emptotal "Employment - Reference Quarter"
label var hira "Hires (All Accessions)"
label var hirn "New Hires"
label var hirr "Recall Hires"
label var sep "Separations (All)"
label var hiraend "End-of-Quarter Hires"
label var hiraendr "End-of-Quarter Hiring Rate"
label var sepbeg "Beginning-of-Quarter Separations"
label var sepbegr "Beginning-of-Quarter Separation Rate"
label var hiras "Hires (All Hires into Full-Quarter Employment)"
label var hirns "New Hires (New Hires into Full-Quarter Employment)"
label var seps "Separations (Flows out of Full-Quarter Employment)"
label var sepsnx "Separations in the Next Quarter (Flows out of Full-Quarter Employment)"
label var turnovrs "Turnover (Stable)"
label var frmjbgn "Firm Job Gains (Job Creation)"
label var frmjbls "Firm Job Loss (Job Destruction)"
label var frmjbc "Firm Job Change (Net Change)"
label var hiraendrepl "Replacement Hires"
```

```
label var hiraendreplr "Replacement Hiring Rate"
label var frmjbgns "Firm Job Gains (Stable)"
label var frmjblss "Firm Job Loss (Stable)"
label var frmjbcs "Firm Job Change (Stable; Net Change)"
label var earns "Average Monthly Earnings (Full-Quarter Employment)"
label var earnbeg "Average Monthly Earnings (Beginning-of-Quarter Employment)"
label var earnhiras "Average Monthly Earnings (All Hires into Full-Quarter Employment)"
label var earnhirns "Average Monthly Earnings (New Hires into Full-Quarter Employment)"
label var earnseps "Average Monthly Earnings (Flows out of Full-Quarter Employment)"
label var payroll "Total Quarterly Payroll"
label var semp "Flag for Beginning-of-Quarter Employment"
label var sempend "Flag for End-of-Quarter Employment"
label var semps "Flag for Full-Quarter Employment (Stable)"
label var sempspv "Flag for Full-Quarter Employment in the Previous Quarter"
label var semptotal "Flag for Employment - Reference Quarter"
label var shira "Flag for Hires (All Accessions)"
label var shirn "Flag for New Hires"
label var shirr "Flag for Recall Hires"
label var ssep "Flag for Separations (All)"
label var shiraend "Flag for End-of-Quarter Hires"
label var shiraendr "Flag for End-of-Quarter Hiring Rate"
label var ssepbeg "Flag for Beginning-of-Quarter Separations"
label var ssepbegr "Flag for Beginning-of-Quarter Separation Rate"
label var shiras "Flag for Hires (All Hires into Full-Quarter Employment)"
label var shirns "Flag for New Hires (New Hires into Full-Quarter Employment)"
label var sseps "Flag for Separations (Flows out of Full-Quarter Employment)"
label var ssepsnx "Flag for Separations in the Next Quarter (Flows out of Full-Quarter Employment)"
label var sturnovrs "Flag for Turnover (Stable)"
label var sfrmjbgn "Flag for Firm Job Gains (Job Creation)"
label var sfrmjbls "Flag for Firm Job Loss (Job Destruction)"
label var sfrmjbc "Flag for Firm Job Change (Net Change)"
label var shiraendrepl "Flag for Replacement Hires"
label var shiraendreplr "Flag for Replacement Hiring Rate"
label var sfrmjbgns "Flag for Firm Job Gains (Stable)"
label var sfrmjblss "Flag for Firm Job Loss (Stable)"
label var sfrmjbcs "Flag for Firm Job Change (Stable; Net Change)"
label var searns "Flag for Average Monthly Earnings (Full-Quarter Employment)"
label var searnbeg "Flag for Average Monthly Earnings (Beginning-of-Quarter Employment)"
label var searnhiras "Flag for Average Monthly Earnings (All Hires into Full-Quarter Employment)"
label var searnhirns "Flag for Average Monthly Earnings (New Hires into Full-Quarter Employment)"
label var searnseps "Flag for Average Monthly Earnings (Flows out of Full-Quarter Employment)"
label var spayroll "Flag for Total Quarterly Payroll"

foreach var in semp-spayroll{
label values `var' flag
}

gen double yrqtr=yq(year, quarter)

gen tech=0
*** Computer manufacturing + semi-conductors

replace tech=1 if industry==3341
*334111 Electronic Computer Manufacturing
*replace tech=1 if ind==334112  //Computer Storage Device Manufacturing
```

```
*replace tech=1 if ind==334118  //Computer Terminal and Other Computer Peripheral Equipment
Manufacturing
replace tech=1 if industry==3342
*replace tech=1 if ind==334220  //Radio and Television Broadcasting and Wireless Communications
Equipment Manufacturing
*replace tech=1 if ind==334290  //Other Communications Equipment Manufacturing
replace tech=1 if industry==3343
*replace tech=1 if ind==334310  //Audio and Video Equipment Manufacturing
replace tech=1 if industry==3344
*replace tech=1 if ind==334413  //Semiconductor and Related Device Manufacturing
*replace tech=1 if ind==334416  //Capacitor, Resistor, Coil, Transformer, and Other Inductor Manufacturing
*replace tech=1 if ind==334417  //Electronic Connector Manufacturing
*replace tech=1 if ind==334418  //Printed Circuit Assembly (Electronic Assembly) Manufacturing
*replace tech=1 if ind==334419  //Other Electronic Component Manufacturing
** IT Industries per the BLS https://www.bls.gov/opub/btn/volume-2/pdf/careers-in-growing-field-of-
information-technology-services.pdf
replace tech=1 if industry==5112
replace tech=1 if industry==5182
replace tech=1 if industry==5415
/*
replace tech=1 if ind==511210   //Software Publishers
replace tech=1 if ind==518210   //Data Processing, Hosting, and Related Services 6695
replace tech=1 if ind==541511   //Custom Computer Programming Services
replace tech=1 if ind==541512   //Computer Systems Design Services
replace tech=1 if ind==541513   //Computer Facilities Management Services
replace tech=1 if ind==541519   //Other Computer Related Services
*/
gen hi=(geography==15)
drop if geography ==11 /** Dropping District of Columbia **/

sort statecode
merge m:1 statecode using temp_nc
drop _m
gen fc_hi_diff=abs(FC09_ml- -.1672194)
egen tag_st=tag(statecode)
egen dfhi_temp=rank(fc_hi_diff) if tag_st==1, track
egen dfhi=max(dfhi_temp) , by(statecode)
drop dfhi_temp fc_hi_diff
label var dfhi "Pre-Ban Ranked Absolute Difference Between Hawaii Enforceability"

gen sepr=sep/emptotal
label var sepr "Separation Rate (All Separations to Total Employment)"
compress

gen post=yrqtr>=222
gen srpost=(yrqtr>=222 & yrqtr<=225)
gen lrpost=(yrqtr>225)
gen i2d=int(industry/100)
egen Tech2d=max(tech), by(i2d)
gen All=1
gen w=emp
global wagevar earns earnhiras earnhirns  earnseps
foreach xx in $wagevar  {
gen ln_`xx' =log(`xx')
local lab: variable label `xx'
label var ln_`xx' "Log `lab' "
```

```
}
gen sepsnxr=sepsnx/(0.5*(emp+empend))
label var sepsnxr "Seperation Rate (From Full Qtr Emp)"
ren ind_level ilevel

gen dfhi40=(dfhi<=40)
gen dfhi50=1

keep if yrqtr>=213 //* keeping only 2013 q2 onwards **/
gen None=1
gen EmpWgt=w
gen ln_emp=log(emp)
gen ln_emptotal=log(emptotal)
gen ln_emps=log(emps)
label var ln_emp "Log Beginning-of-Quarter Employment"
label var ln_emptotal "Log Employment-Reference Quarter"
label var ln_emps "Log Full Quarter Employment (Stable)"

egen stateyrqtr=group(statecode yrqtr)
egen stateind=group(statecode industry)
egen indyrqtr=group(industry yrqtr)

egen stateXtech=group(statecode tech)

save temp_qwi_fin, replace


***PROGRAM 2: Create_Tables_Figures.do***

*cd \workingdirectory\ /**<- Change this to the directory of the raw data file **/

/****/
/**
https://lehd.ces.census.gov/data/schema/latest/lehd_public_use_schema.html#_national_qwi_and_state_leve
l_qwi_qwipu
**/

global csif "if edcode ==0 & tech==1"
global wsif "if edcode ==0 & hi==1"
global csdum hi
global wsdum tech
global csclust statecode
global wsclust ind
global dddclust statecode

global csdes "Cross-State, Within-Tech"
global wsdes "Within-Hawaii, Cross-Industry"
global ddddes "Triple Difference Analysis"

global wsdd Tech
global csdd Hawaii
global ddddd Hawaii


global abws "i.ind i.yrqtr"
global abcs "i.ind##i.yrqtr i.statecode##i.ind"
```

```
/***********************************************************************************/
/********Setup for binscatter analysis ***************/
/***********************************************************************************/
foreach yy in ws cs {
	use sepr sepbegr earns earnhiras emp emptotal emps yrqtr statecode edcode industry w hi tech dfhi
///
		Tech2d geography stateXtech using temp_qwi_fin ${`yy'if}, clear
	gen old_$`yy'clust=$`yy'clust
	replace $`yy'clust=0 if ${`yy'dum}==1 /*** To make the treated industry/state as group =0 ***/
	foreach xx in sepr sepbegr earns earnhiras  emp emptotal emps {
		local lab`xx': variable label `xx'
	}

	collapse (first) dfhi  geography (mean) old_${`yy'clust} w ///
		Tech2d hi tech  sepr sepbegr earns earnhiras emp emptotal emps [aw=w], ///
		by(${`yy'clust} yrqtr)

		foreach xx in sepr sepbegr earns earnhiras  emp emps emptotal {
			label var `xx' "`lab`xx''"
		}
	gen ln_earns=log(earns)
	gen ln_earnhiras=log(earnhiras)
	gen ln_emp=log(emp)
	gen ln_emptotal=log(emptotal)
	gen ln_emps=log(emps)
	label var ln_emp "Log `labemp' "
	label var ln_emptotal "Log `labemptotal'"
	label var ln_emps "Log `labemps'"
	label var ln_earns " Log `labearns'"
	label var ln_earnhiras " Log `labearnhiras'"

	egen grtreat=group(${`yy'clust})
	tsset grtreat yrqtr
	egen ct=count(yrqtr), by(grtreat)
	keep if ct==16
	format yrqtr %tq
	xtdes
	label var sepr "Overall Separation Rate"
	label var sepbegr "Beginning-of-Quarter Separation Rate"
	label var ln_earns "Log Overall Avg Monthly Earnings"
	label var ln_earnhiras "Log Hires Avg Monthly Earnings"
	label var ln_emp "Log Beginning-of-Quarter Employment"
	label var ln_emptotal "Log Employment-Reference Quarter"

save temp_qwi_synth_`yy', replace
}


/***********************************************************/
/*** Binscatter analysis -- **/
/***********************************************************/
ssc install binscatter, replace

foreach yy in ws cs {
```

```
	use temp_qwi_synth_`yy' , clear
		foreach xx in ln_earns ln_earnhiras sepr sepbegr {
			local lab: variable label `xx'  /* <- save variable label in local `lab'*/
			binscatter `xx' yrqtr [aw=w], n(16) absorb(${`yy'clust}) by(${`yy'dum})  ///
			m(o Th  Sh ) legend( lab(1 "Other") ///
			lab(2 "${`yy'dd}") rows(1) size(small)) rd(221.1) ///
			line(connect) xlabel(213(3)228,format(%tq) labsize(small)) xtitle("")  ytitle("")  ///
			t2("`lab'", size(small)) title("${`yy'des}", size(small)) ///
	savegraph(qwi_bs_`yy'_collwtd_`xx'.gph)
}
}

/** Figure 1 ******/
**QWI Earnings Variables: Binned Scatter Plots
graph combine qwi_bs_ws_collwtd_ln_earns.gph qwi_bs_ws_collwtd_ln_earnhiras.gph ///
	qwi_bs_cs_collwtd_ln_earns.gph qwi_bs_cs_collwtd_ln_earnhiras.gph , ///
	saving(Figure1_qwi_bs_earn_collwtd_all.gph, replace) graphregion(color(white)) ///
	title("QWI Earnings Trends", size(small))
graph save "Figure1_qwi_bs_earn_collwtd_all.gph", replace
graph export "Figure1_qwi_bs_earn_collwtd_all.png", as(png) replace

/** Figure 2 ******/
**QWI Mobility Variables: Binned Scatter Plots
graph combine qwi_bs_ws_collwtd_sepr.gph qwi_bs_ws_collwtd_sepbegr.gph ///
	qwi_bs_cs_collwtd_sepr.gph qwi_bs_cs_collwtd_sepbegr.gph , ///
	saving(Figure2_qwi_bs_mob_collwtd_all.gph, replace) graphregion(color(white)) ///
	title("QWI Mobility Trends", size(small))
graph save "Figure2_qwi_bs_mob_collwtd_all.gph",  replace
graph export "Figure2_qwi_bs_mob_collwtd_all.png", as(png) replace

/************************************************************/
**Tables 1 and 2: DID Analysis
/************************************************************/
ssc install outreg2, replace
ssc install reghdfe, replace
ssc install ftools, replace


/************************************************************/
/** First -Cross-industry within Hawaii**/
/************************************************************/
capture program drop myregs_within_hi
program define myregs_within_hi
use temp_qwi_fin if edcode==0 & hi==1, clear
ren industry ind
gen postXtech=post*tech
gen srpostXtech=srpost*tech
gen lrpostXtech=lrpost*tech
global interws1 postXtech
global interws2 srpostXtech lrpostXtech
global out outreg2 using "`2'.xls",
local replace replace
foreach y in  ${`1'} {
foreach sample in Tech2d All {
foreach int in interws1 interws2 {
reghdfe `y' ${`int'} if `sample'==1 [aw=EmpWgt], cl(ind) absorb(i.ind i.yrqtr)
```

```
$out  `replace' ctitle(`y') addtext(Industry FE, Yes, Quarter FE, Yes, Sample, `sample', ///
Weights, EmpWgt, DV, `y', SE Clustered By, Industry)
local replace
}
}
}
end

/**************************************************************/
/** Next -Cross-state within Tech**/
/**************************************************************/
capture program drop myregs_within_tech
program define myregs_within_tech
use temp_qwi_fin if edcode==0 & tech==1, clear
ren industry ind
gen postXhi=post*hi
gen srpostXhi=srpost*hi
gen lrpostXhi=lrpost*hi
global intercs1 postXhi
global intercs2 srpostXhi lrpostXhi
global out outreg2 using "`2'.xls",
local replace replace
foreach y in  ${`1'} {
foreach sample in dfhi40 dfhi50  {
foreach int in intercs1 intercs2 {
reghdfe `y' ${`int'} if `sample'==1 [aw=EmpWgt ], cl(statecode) absorb(i.ind##i.yrqtr i.statecode##i.ind)
$out `replace' ctitle(`y') addtext(Sample, `sample', Weights, EmpWgt , DV, `y', SE Clustered By, State, Ind X
Qtr, Yes,  State X Ind, Yes )
local replace
}
}
}
end
/**************************************************************/
global lnevars ln_earns ln_earnhiras
global mobvars sepr sepbegr

myregs_within_hi lnevars Table1_panelA_QWI_DID
myregs_within_tech lnevars Table1_panelB_QWI_DID

myregs_within_hi mobvars Table2_panelA_QWI_DID
myregs_within_tech mobvars Table2_panelB_QWI_DID

/***********************************************/
/***Table 3 DDD Analysis****************/
/***********************************************/
global out outreg2 using "Table3_QWI_DDD.xls",
local replace replace
use temp_qwi_fin if edcode==0,  clear /**Keeps all workers**/
foreach hh in post srpost lrpost {
gen `hh'XhiXtech=`hh'*hi*tech
gen `hh'Xhi=`hh'*hi
gen `hh'Xtech=`hh'*tech
}
gen hiXtech=hi*tech
```

```
/** With Ind X Year-Qtr FE, State X Ind and State X Year-Qtr Fixed effects, only the following inetractions are
identified (verified that all other direct terms and interactions are absorbed by the fixed effects) **/
global interddd1_sh postXhiXtech
global interddd2_sh srpostXhiXtech lrpostXhiXtech

ren industry ind
foreach y in   ln_earns ln_earnhiras sepr sepbegr {
foreach sample in dfhi40 dfhi50  {
foreach int in interddd1_sh interddd2_sh {
foreach wt in EmpWgt {
reghdfe `y' ${`int'} if `sample'==1 [aw=`wt'], cl(statecode) absorb(indyrqtr stateyrqtr stateind)
$out `replace' ctitle(`y') addtext(Industry FE, NA, Quarter FE, NA, Sample, `sample', ///
Weights, `wt', DV, `y', SE Clustered By, State, State FE, NA, Ind X Qtr, Yes,  State X Ind, Yes, State X Qtr,
Yes )
local replace
}
}
}
}

/***********************************************/
/***Appendix Table 1 ***************/
/***********************************************/
global ddhi HI_tech
global ddtech tech_HI
global ffhi tech
global fftech hi
foreach yy in hi tech {
foreach xx in emp  hirn sep {
use temp_qwi_fin if edcode ==0 & `yy'==1, clear
gen yr_qtr=year*100+quarter
drop if yr_qtr==201702
collapse (mean) post (sum) `xx', by(yr_qtr ${ff`yy'})
collapse (mean) `xx', by(post ${ff`yy'})
reshape wide `xx', i(post) j(${ff`yy'})
renpfix `xx' ${dd`yy'}
gen str10 var="`xx'"
order var
tempfile t`xx'
save `t`xx''
}
use `temp', clear
append using `thirn'
append using `tsep'
gen total_`yy'=${dd`yy'}0+ ${dd`yy'}1
replace ${dd`yy'}0=round(${dd`yy'}0,1)
replace ${dd`yy'}1=round(${dd`yy'}1,1)
replace total=round(total,1)
sort var post
tempfile temp_`yy'
save `temp_`yy'', replace
}
use `temp_hi'
merge 1:1 var post using `temp_tech'
drop _m
export excel using Appendix_Table1.xls, replace
```