Non-Compete Agreements and Compensation Structure in the Technology Industry
Thuc Doan Nguyen, Miami University

I. Introduction

Gone is the era of non-compete agreements being the exclusive concern for CEOs, executives, or higher-ranked employees in general. Non-compete agreements (NCAs) are legal covenants preventing employees from entering into markets or professions in direct competition with their previous employer, and recent news articles have brought light to the fact that even interns fresh from college are increasingly being asked to sign NCAs[1]. These are said to harm young people's job prospects even before the first step towards their future careers.

One important fact about NCAs is that the degree to which they are enforceable differs by state. For instance, historical aspects of California's legal system have long made it almost impossible for firms to enforce such agreements there (Fallick et al. 2005). The state's distinct approach towards NCAs is a unique discussion topic among economists who investigate high employee mobility as a source of agglomeration economies (or external economies of scale) in Silicon Valley's computer industry. While existing papers have discussed how California's ban on NCAs deprived Silicon Valley employers of a powerful tool to prevent costly mobility and led to the region's growth (Gilson 1998, Hyde 2003, Fallick et al. 2005), little to no research has been done to explain the relationship between varying degrees of NCA enforceability in many different states and the structure of pay. I hypothesize that the inability to enforce NCAs will alter the mix of compensation types because stock and bonus reduce turnover in a different way from regular salaries. Stock is a form of compensation that is usually not vested immediately and ties workers more strongly to firm, whereas salaries are more easily imitated and if pay rises industry-wide, then higher pay alone does not help retention or performance. Bonus, on the other hand, is productivity-based and encourages workers to exert efforts. From the employer's perspective, if the goal of using stocks and bonuses is to motivate workers to work as hard as they can, one would expect the use of these compensation forms to increase when NCAs are enforceable. By contrast, if stocks and bonuses are mostly needed as retention devices, one may expect their use to decrease if NCAs are enforceable and available at almost no charge to firms. The focus of this paper being technology sector is further motivated by the fact that: besides the usual base salary and bonus, technology firms are known for compensating workers with stock ownership, which helps employees feel invested in their companies. This ultimately leads to the first question this paper addresses: does pay composition (bonus/stock versus base salary) in the technology industry vary with levels of NCA enforceability in different states?

Another issue I would like to address in this paper is to identify whether NCAs and other contract components are complements or substitutes. Kryscynski and Starr (2019) lay foundation to this approach by defining the two types of mobility constraints firms used: premium and punitive constraints. Premium constraints are positive sources of utility offered to workers such as performance rewards or amenities, while punitive constraints are penalties incurred should they opt to leave such as NCAs, bonus repayment provisions, or repayment penalties. A positive correlation between premium and punitive constraints then would serve as evidence of a complementary relationship between the two. A complementary relationship may exist for a number of reasons: first, with an enforceable NCA, a firm may be more willing to invest in

training employees, plus research and development, because they avoid the hold-up problem (i.e., that firms are unwilling to invest in workers who may leave their job for a competitor: see Williamson 1979). This encourages the employers to strive to protect their investment even more by giving bonuses as it is now a more valuable investment. In other words, punitive and premium constraints act as complements because the value of protecting the asset increases. Second, firms may need to offer perks to outweigh the costs of an employee bearing an NCA. NCAs also disincentivize effort: realizing that effort incentives are low, firms may offer perks and benefits to keep workers motivated. By contrast, premium and punitive constraints may be substitutes. Balasubramanian et al. (2019) claimed that workers in an average-enforceability state receive lower cumulative earnings relative to equivalent workers in a non-enforcing state. This may be the case if, in order to retain employees, when firms cannot use punitive constraints, they will use premium ones instead. Inversely, if firms have the choice between NCAs and premium constraints to reduce mobility, and NCAs are much "cheaper" (available due to strict enforceability, unlike costly bonuses), then employers will just use NCAs in lieu of bonus or stock compensation.

After examining pay structure among tech employees, I show that premium constraints are substitutes for NCAs with respect to employee retention. I observe lower total monetary earnings in states that more effectively enforce non-compete clauses, which translates to NCAs potentially being a factor that contributes to firm's applying monopsony power and keeping pay low. In this paper, the effect is discovered to be more profound for women than it is for men. Applying this theory to the case of California, if employers learn that they cannot prevent high velocity employee movement and knowledge spillovers by using NCAs, they may adopt a different strategy: using premium constraints as substitutes for punitive constraints. This novel contribution to the literature helps us understand the dynamics between two different types of mobility constraints and the degree to which firms use one type of constraint when the other is more (or less) available. Furthermore, I find some evidence that not only does total compensation reduce, but the percentage of incentive pay also decreases as a result of being subject to a stricter NCA enforcement regime. This finding raises the question of whether productivity-based compensation is effectively fulfilling its role to increase earnings for tech employees who, having signed NCAs, have less bargaining power in subsequent negotiations, and probably already on the path of flattening their earnings profiles for the rest of future careers.

II.   Literature Review

The incentives that firms have to offer are said to include both financial compensation and nonfinancial practices (Chadwick and Dabu 2009). Reiche (2008) acknowledges that, while monetary incentives are crucial for retention, they are easily imitated by other firms and thus insufficient to dissuade employees from competing job offers. Implicit to classic literature on retention practices seems to be the idea that considering a holistic scope of human resource (HR) methods will create synergy. Much research has been devoted to studying HR practices' interplay as complements and how they support each other (Chadwick 2010, Wei 2006, Baird and Meshoulam 1988). In addition, Khair and Saeed (2011) empirically demonstrated that internally consistent and complementary HR methods are more able to enhance organizational performance than a sum of individual ones. As the saying goes: "the whole is greater than the sum of its parts", a more salient outcome is produced when practices complement one another (Delery and Doty 1996). The implied prescription, it seems, is to adopt as many mobility constraints as possible, conditional on the benefits outweighing the costs of these constraints.

Kryscynski and Starr (2019), however, contend that this simple "more is better" prescription is potentially misleading and show that it would only retain a non-productive workforce. Furthermore, implementing a system comprised of various constraints can impose real costs on firms. Considering that retaining human resources should be at a cost below the economic value that they add to the firm (Coff 1997), it is worth also considering substitution of one constraint for another.

Literature surrounding the effect of non-competes on wages is small, according to the 2016 report "Non-compete Contracts: Economic Effects and Policy Implications" by the Office of Economic Policy at U.S. Department of the Treasury. Furthermore, previous studies on NCAs have mostly focused on how their enforceability affects the size of compensation bundles as a whole (Kryscynski and Starr 2019, Balasubramanian et al. 2019, Garmaise 2011), as opposed to comparing each component's role in the overall package. One important finding in a previous study (Balasubramanian et al. 2019) is that, compared to peers in low NCA enforceability states, workers in states with high enforceability are compensated with reduced wages in their current job as well as throughout the rest of their career. However, the paper does not delve into exactly how each of the various components (i.e. stock, bonus or base salary) in the payment package reacts given this overall reduction. Is it the case that all of these three elements shrink as a result of this contraction, or did any actually manage to increase its representation? What Balasubramanian et al. (2019) demonstrated is that NCAs can hold down pay because firms do not have an incentive to raise earnings. In this paper, however, I attempt to show firms do not use premium constraints to complement punitive constraints, even though theory favoring complementarity predicts they further incentivize workers to achieve optimal effort levels. Although higher salaries may act as a premium constraint to some extent, there may not be any clear impact on effort, and if pay rises industry-wide, higher pay alone does not help retention or performance. Stocks and bonuses do, in different ways, because they incentivize workers to exert effort, making them another type of substitute for NCAs.

Even when research has been done to investigate the relationship between NCAs and compensation structure, little effort has been made to understand this topic in the technology industry specifically. For instance, Lavetti et al. (2019), studying physician compensation, established that the share of total earnings that is tied to individual productivity is more than twice as high for physicians with NCAs. Their theoretical model underlying the role of incentive pay in promoting earnings despite a reduction in bargaining power caused by NCAs, has only been applied to the empirical test focusing on primary care physicians alone. Although the NCA-related questions they initially seek to answer apply more generally to firms that provide high-skilled services, many areas of profession besides doctors are left un-explored, of which the technology industry is a prime example.

III. Theory

If wages are higher in locations with stricter NCA law, it would appear that NCAs have solved the investment hold-up problem, incentivizing firms to promote productivity by investing in technology advancements, acquiring valuable information and most importantly, providing employee training. Due to bargaining, the firm is not the full residual claimant of the additional returns generated by its investment, and the hold-up problem occurs if firms' investment in capital is potentially held-up by the worker (Acemoglu 2011). Without binding contracts (as is in the case of California), a firm could be disincentivized to train due to the "hold-up" threat:

knowing that once investments in human resources have been made, employees can threaten to use their earned skills in a way that is not optimal for the firm which initially employed them. This could mean demanding renegotiation or job-hopping to another company and leaking information. This theory partly explains the grim view presented in Hyde (2003) of Silicon Valley as a place providing "inadequate incentives for training". Better-trained workers are equipped to perform more productively, while being more motivated, and are eager to take on duties (Ali et al. 2017). As such, firms' investments are quite valuable. Investment then encourages firms to want to protect their assets even more by being generous with monetary compensations and similar utility-creating constraints. It may also be the case that firms are using premium constraints to incentivize efforts diminished by punitive constraints. Imposing punishments for leaving in the form of NCAs, or similar non-solicitation agreements', may discourage workers from exerting full effort (Garmaise 2011). If that is the case, then the firm is essentially holding on to a less-than-fully productive workforce (Kryscynski and Starr 2019), so to counteract that negative impact and prevent it from hurting their pursuit of rents, firms can offer performance-based monetary incentives. Higher wages then can be considered as payment for the worker who sacrificed their mobility. On the flip side, when a firm signals economic commitment to workers by offering premium benefits, the value of protecting its human capital also increases. Employees who receive learning incentives and feel invested in their companies via stock can also be motivated and absorb training more quickly if firms choose to provide them. To garner rents from training, firms must find ways to limit the imitability and mobility of their resulting human capital (Chadwick and Dabu 2009). As a result, firms would want to adopt NCAs to guard against loss of value due to employees' departure. Rubin and Shedd (1981) have also advocated that NCAs should be enforceable to help protect employers' investment when they provide general knowledge that is too expensive for workers to pay for.

The previous paragraph has summed up the hypothesis that NCAs/punitive constraints and premium constraints are complementary because the value of protecting the asset increases. However, I actually found evidence of a substitution relationship instead. Balasubramanian et al. (2019) also observed that compensation is lower in states that enforce NCAs in both their current and subsequent jobs, coupled with increased employment durations or "job spells". This suggests that effective NCA law locks workers into their jobs, preventing them from earning the maximum possible wage and working where they want. This points towards punitive and premium constraints being substitutes from the employer's perspective. One can think of the NCA in this situation somewhat similar to the National Football League's exclusive franchise tag on a player that is crucial to the team's success. Usually reserved for players of great potential, a franchise tag allows a team's manager to strategically retain valuable free-agent players for a year without exceeding the League's salary cap. Without the tag, the team may have no other way to hold onto their best player once he hits the market due to all the competing offers. For a really good player, the franchise salary could be less than what they would command on the open market. Most importantly, the threat of being forced to sign the franchise tender usually tilts the leverage in favor of the team, causing some players to accept contracts for less money than they would attract otherwise. Back to the case of California, if firms cannot use legal means for retention, they will instead use premium constraints since high turnover is costly in general. Moreover, in this high-velocity labor market, employees should exhibit maximum incentives to produce innovative information, or value worthy of firm's protection since they know that they may be on the job market themselves in the near future (Hyde 2003). Inversely, if firms' goal is to reduce mobility and they can choose between NCAs and financial rewards, since NCAs are

"cheaper" (available at almost no cost to firms given strict enforceability), then employers will just use NCAs as substitutes for other constraints. Given that writing bonus checks and awarding stocks can be quite expensive to firms, they may also believe that the potential benefit from incentivizing the extra efforts diminished by NCAs does not outweigh the cost. One may raise the question of why being asked to sign NCAs does not cause workers to bargain for higher wages in consideration of future employment restrictions. In response to this, Marx (2011) argues that firms are still strategically able to keep pay down by managing the process of getting workers to sign these contracts, waiting for workers' bargaining position to weaken (most of the time, firms do not present the contract until after applicants have accepted the position). It may as well be the case that only later when the worker considers exiting a firm, does he or she become aware of the existence or implications of the NCA. Starr et al. (2017) finds that about a third of workers do not even know if they are bound by a non-compete, and that only 30% of employees have another offer at the time they were asked to sign. It is almost impossible to expect workers to reach the best possible deal given incomplete information, lack of alternative options, and lack of negotiation. Finally, even if firms may initially use higher wages to coax new employees into signing an NCA before locking them in (i.e. the net effect on wages could be positive in earlier years), finding significant and negative coefficients in my results here means the net effect is negative in later years and remains negative on average. Besides training, protecting trade secrets and "screening" (preferentially hiring workers with low likelihood of departure), a 2016 report by the Office of Economic Policy at U.S. Department of the Treasury claimed that another possible rationale behind firms' use of NCAs is "lack of salience". This applies when employers exploit the fact that employees do not pay attention to non-competes and do not realize how much bargaining power or chances of future employment they are foregoing. If lack of salience is the dominant explanation, we would expect no initial wage premium and slower wage growth, as workers are prevented from taking advantage of outside opportunities or using these opportunities as leverage for wage growth at their current firm (on the other hand, if screening is the dominant explanation, we may expect stricter enforcement to cause an initial wage premium but slower subsequent wage growth nonetheless).

IV.   Data

The purpose of this study is to investigate the relationship between salary structure and NCA enforceability, so we need a cross-sectional dataset which contains salary structure information and merge it with a second set that contains indicators for inter-state variation in enforcement scores. Previous research on the topic of pay composition has been challenged with the difficulties to pinpoint the makeup of pay, given lack of data. This paper attempts to offer a source for the former dataset from the public Levels.fyi website, which maps tech career levels and tabulates compensation breakdown. This online survey contains micro-level information on compensation and career projections for tech workers. Besides having data from every state in the U.S., it also has participants from overseas, but for the purpose of this paper and since variation in laws that govern NCAs is only known at state level, we will limited our analysis to U.S. locations. The second set used for analysis is the NCA index scores by state which stems from a legal database constructed in Bishara (2011) that quantifies the relative strength of NCA enforceability across states. This serves as the source of variation in the restrictiveness of NCAs. Both components used in the analysis are to be presented with greater details later in this section.

A. Compensation data

This dataset describes the compensation of workers in the technology industry, broken out into different components of pay: base salary, stock grant value and bonus. Stock grants can be regarded as a powerful motivator in employee retention by granting workers shares of stock that are vested (or become unconditionally owned) after a fixed number of years. Generally, the goal of equity compensation can be to align workers' incentives with the company's. If the worker leaves prior to vesting, he loses his stock in the firm. Levels.fyi, an Information Services company established in 2017 which created this data source, displays a worker's stock compensation as divided by the number of years it takes for the grant to fully vest. For most companies here, the equity reported is either pure grant or Restricted Stock Units that represent equity value in terms of a dollar amount and do not require a purchase like stock options (options to buy a part of the company via common stock, which also have a vesting schedule and their annual stock value can be measured from the latest valuation of the company). In an effort to bring transparency to the workplace, the website also offers a visual tool where you can see reports on crowdsourced salary information, input by individual users with the date and time of submission recorded. The two co-founders shared how the website was established and used during a talk published on June 15, 2019, "Here's How Big Tech Companies Like Google and Facebook Set Salaries for Software Engineers" on CNBC. Essentially, it allows people to drill down into specific data points, including the submitter's work specialty and location. The dataset pulled from this website and currently being used for this report was last updated on January 2, 2020. After data cleaning (to remove observations with incomplete information and standardize), keeping only locations in the U.S., we arrived at 9,522 observations from 2017 to the beginning of 2020. Given the large concentration in Silicon Valley's computer industry, Californians also represent a majority of the data.

To submit your compensation, you can either upload an offer letter/pay document, or enter numbers in manually, which is then validated by verified data. To manually complete a submission, contributors must input company name, location (City, State), years of experience, years at company, level, title, area of focus/specialty, and total compensation yearly (as found on W2). You can also further break down the submitted value by base salary, stock, and bonus. As you enter numbers for all three components (base salary, stock, and bonus), if the sum does not match up to the total compensation, the system will give you an error message. These numbers exclude any not-discussed fringe benefits like pensions, 401Ks or health insurance. Other optional items include gender, and further details like if you have a PhD or Master's degree. We do not know whether workers have NCAs and it is worth reemphasizing that this paper does not discuss the effect of NCAs on an individual level. The key independent variable here is the degree to which NCAs are enforceable at a given state and thus different at a state level. Total yearly compensation is required for all submitted entries and capped between 10,000 and 5 million U.S. dollars. I have also calculated non-base salary, a continuous variable that is the sum of bonus and stock. "Bonus" here refers to target amount for a year and is money, which is different from stock. Table 1 presents descriptive statistics for our aforementioned financial components of compensation. Despite claims to have been validated, since the data is crowdsourced, it could raise some concerns, including a self-selecting population: the people most likely to submit their compensation details are those that make a lot of money. Nonetheless, if selection bias into inputting the data is not related to NCA enforceability then the relationship we are exploring should not be affected. Additionally, I did find a wide range of compensations submitted, and our final sample represents about 600 job titles and over a thousand companies of different sizes. The founders of the website also stand behind how they remove outliers and

unreliable data points, saying it matches up closely with similar compensation datasets that Radford or Connery Consulting sell[2]. These are HR consulting firms that survey and benchmark base salaries, incentives, equity awards and more to design recruitment practice and help hire talents.

B. Enforcement index

The data source for the measure of NCA enforceability that we will use in our analysis is built upon Norman Bishara's quantification of various dimensions of NCA enforceability for each state: State Statute of General Applicability, Employer's Protectable Interest, Plaintiff Burden of Proof, Modification or Blue Pencil, Enforceable if Employer Terminates, Change In Terms/Continued Employment Sufficient Consideration for NCA, and Start of Employment Sufficient Consideration for NCA (see Bishara 2011 for a review). This dataset has been used by economists researching the topic of NCA and was used by Lavetti et al. (2019) to show that state enforceability is strongly predictive of NCA use. This led them to conclude that firms are less willing to impose an NCA in a state where it is unlikely to be enforced. The higher the index score, the higher the chance of a court upholding an NCA in a given state, where 0 refers to absolutely no likelihood of upholding an NCA. For example, given that most overall scores are above 100 and the maximum is 470, California has a very low score (31), meaning the law is almost unenforceable there (see Appendix Table A1 for scores by state). This index captures NCA enforceability along a spectrum of weak to strong enforceability.

I standardized the enforceability index to have a minimum of 0 and a maximum of 1, according to the formula in Equation (1) below. By using this min-max scalar, the data is scaled to a fixed range, increasing interpretability. We know that the actual minimum and maximum scores of all the 50 states are 0 and 470. A min-max scaling is mathematically done by subtracting the minimum value from the value, then divided by the overall range. For example, let λ be a given state's score using Bishara's system. In order to standardize these numbers, we will use a formula as follows, where λ_s represents the standardized score:

(1)
$$\lambda_s = \frac{\lambda - 0}{470 - 0} = \frac{\lambda}{470}$$

C. Descriptive plots of merged data

Figures 1, 2, and 3 are binned scatterplots of different types of compensations against standardized NCA scores of each state. These binned scatterplots are used to help with visualization, instead of a normal densely-plotted scatter diagram. They are created by grouping the x-axis variable into equal sized bins and then marking points whose coordinates correspond to the means of the x and y variables within each bin. A regression line is also drawn across each graph. A pattern of substitution between each type of compensation and NCAs would generate a downward sloping line and an upward sloping line in the case of complements.

From the graphs, we can see early indications of NCA's restrictiveness potentially being substituted for monetary constraints. This trend appears to persist more strongly in the context of total yearly wages (slope=-87.3) than it does with non-base (slope=-48.6) and base salaries (slope=-37.4). Yet, everything so far may just indicate that dominant states like California (standard score=0.07) pay more and perhaps have more skilled workers so next, I will formally test whether this relationship is statistically significant using econometrics methods.

V.   Empirical Strategy

In this section, I describe the key variables as well as regressions performed. To determine the effect of the enforceability index on both the size and proportion of each financial payment type to the total sum, I used a model that accounts for fixed effects for each company, job title and other factors. Thanks to the nature of the data, I was able to pinpoint exactly the names of firms instead of just their characteristics, and thus able to bring in firm fixed effect (this strategy is sometimes called the method of Abowd, Kramarz, and Margolis or "AKM"; see Abowd, Kramarz, and Margolis 1999). First, I take the natural log of all the payment types to avoid undue influence of outliers, and to interpret output in percentage terms (zero values of stock and bonus are handled by adding one dollar to each observation before taking the log). I also calculated the percentage of each component compared to total yearly compensation. The standard errors are clustered by state to account for serial correlation among the error terms within each state, while assuming that there is no significant time effect from middle 2017 to 2018 to 2019 (which is when the data is gathered). Allowing for correlation of residuals within a state across people, this clustering is particularly important given that the NCA index is measured at the state level. I will estimate our model in the simplest form first (Equation (2)), then add in more fixed effects later:

(2) $Y_{ijcps} = \alpha + \beta_1 SCORE_s + \beta_2 YEARSOFEXP_i + \beta_3 YEARSATCOMPANY_i + \beta_4 FEMALE_i + \varepsilon_{ijcps}$

SCORE is the continuous NCA variable and β_1 is the coefficient of interest, measuring the effect of enforcement score. Y_{ijcps} represents a salary-related characteristic of interest for individual i given job title j, specialty p, at company c and in state s. Nine variations of this model differ from each other by their dependent variable Y_{ijcps}: log of total compensation, log of base salary, log of stock grant value, log of bonus, log of non-base compensation (i.e. stock-plus-bonus combined), and percentage of individual component to the total payment. Y_{ijcps} depends on experience of the worker (YEARSOFEXP), tenure at company (YEARSATCOMPANY) and gender of worker (FEMALE is a dummy variable that equals 1 if the person is a woman). Given the simple model, one may point out the problem of covariance between regressors and the unobservables, ε_{ijcps}. According to Lavetti et al. (2019), frictional job search or matching can lead to the error term being correlated with our regressors. This leads to the decomposition of the unobservables:

(3) $\varepsilon_{ijcps} = \mu_i + \varphi_c + u_{ic}$

Where μ_i encompasses unobserved worker effect that accounts for people's differences in earnings capacity (like ability). φ_c is an unobserved firm effect, and u_{ic} is the residual. An example of correlation between tenure and φ_c would be if employees are less likely to leave once they acquire a job at high earning firm. Thus, it is very important to include company fixed effect to assuage endogeneity bias due to firms' unobservables like managerial ability. Without this fixed effect, our results could conflate the differential allocation of firms across states that have varying enforcement regimes. An example would be if firms try to locate in states that enforce NCAs very strictly. If that is the case, regressing outcomes on enforceability would just inform whether those particular firms pay more, or use more bonus and equity. It is still informative, but there may be other differences about those firms. In Lavetti et al. (2019), without observing the exact name of firm/practice, the paper relied on empirical methods and failed to reject the null hypothesis that unobserved firm characteristics are uncorrelated with earnings growth or NCA use. This ultimately leads us to the first expansion of our model:

(4) $Y_{ijcps} = \alpha + \beta_1 SCORE_s + \beta_2 YEARSOFEXP_i + \beta_3 YEARSATCOMPANY_i + \beta_4 FEMALE_i + w_c + \varepsilon_{ijcps}$

where w_c represents fixed effects for company. Next, I will also include job specialty (or area of focus) and title fixed effects. This will allow the model to estimate effects within-specialty and within-title, as title and area of focus do matter for earnings and compensation structure (even though doing so may significantly deplete the power of the regression). For example, someone with an executive title may have more of their earnings in equity (and probably has more access to stock shares as well), compared to a junior web designer. Similarly, a tech employee whose focus is business operations or business intelligence may also be more interested in building their wealth from stock grants than someone whose focus is algorithms. Our model then expands to:

(5) $Y_{ijcps} = \alpha + \beta_1 SCORE_s + \beta_2 YEARSOFEXP_i + \beta_3 YEARSATCOMPANY_i + \beta_4 FEMALE_i + w_c + v_p + z_j + \varepsilon_{ijcps}$

The variables v_p and z_j are fixed effects for area of focus and title, in that order. At this point, there is still a dangerous confounder yet to discuss: geography. This is because we are unable to control for state, and outcomes could vary at the state level, regardless of whether we are within company or within job title. In theory, even if we have controlled for everything, our regression results may just stand testimony to the fact that different parts of the country are, indeed, different. This motivates me to create a new variable called division based on how the United States Census Bureau allocates states into nine divisions (so that about 5 or 6 states are grouped into one division on average, see more details on these divisions in Appendix Table A2). Using this new variable, I added a division fixed effect term to compare geographically similar neighbors (g_d):

(6) $Y_{ijcps} = \alpha + \beta_1 SCORE_s + \beta_2 YEARSOFEXP_i + \beta_3 YEARSATCOMPANY_i + \beta_4 FEMALE_i + w_c + v_p + z_j + g_d + \varepsilon_{ijcps}$

Then, the regression would be comparing observations from one to nearby states, which may be a more honest comparison. If there is still a significant effect, that would bolster the empirical strategy given that the estimates are also within-firm, within-job title and within-specialty with other controls. I should note that we are not controlling for state dummies so cross-state differences that are correlated with NCA enforceability can drive regression coefficients. Lavetti et al. (2019), during discussion of this correlation, have used empirical evidence to show that the extent to which this maybe a concern is limited: the enforceability of NCA laws is, on average, uncorrelated with the political preferences of states. Hausman and Lavetti (2019) also find that NCA laws are uncorrelated with unemployment rates, population levels, views about the size of government, to name but a few.

A potential concern of selection on quality could arise if workers respond to changes in state NCA laws when it comes to geographic locations, meaning that the heterogeneity in earnings effects of NCAs is likely to be driven by geographic sorting. Unobserved person-specific traits such as ability can cause talented workers to move to California, famed for its refusal to recognize these agreements. My first argument is that California and its Silicon Valley are the dream workplace coveted by all, and the demand for technical labor there is still in such deficit that there are much void to be filled by any level of ability. Assuming the lowest level to enter this high-skilled sector is that you need at least bachelor degree or some experience, many college degree holders in computer science flock to the West in huge movement and yet it is still

not enough. Extending projections of California's workforce skills through 2030, Johnson et al. (2015) find that the state will fall about 1.1 million college graduates short of economic demand, if current trends persist. Even the arrival of highly educated workers from elsewhere is unlikely to be large enough to fill this gap. California has many high-tech innovation centers, granted, but the state is, and will continue to be the birthplace for many start-ups with job openings for both seasoned workers and young graduates alike. True to its name, the tech boom here does not lack opportunities: the market is not saturated but keeps expanding still with new tech jobs year-over-year, and supply in California is predicted to not outlast demand. It is also the state with most net tech employment job gains in 2018, according to the Computing Technology Industry Association's 2019 report.

Nonetheless, even though we have already accounted for division fixed effect, I address the matter further by running our regression on a subsample without California. It would be very strong evidence if the relationship still holds assuming that there is no potential correlation between the use of NCAs and worker quality among the remaining states outside of California. This assumption of no systematic differences in quality based on the use of NCAs outside California seems fair, since no other state possesses both an outstanding fame for its level of computer human resources and an extreme level of NCA enforcement. I tested whether this is true, using Bloomberg 2019 U.S. Innovation index[3] as proxy for quality, and used The Computing Technology Industry Association 2019 research report - "The definitive guide to the U.S. tech industry and tech workforce", to calculate tech gross state product (GSP) per employed person as proxy for productivity. I did not find any significant result as to indicate a relationship between rankings of NCA scores and innovation, nor for productivity (see Table A3 for this result). Behind California, Seattle in Washington is usually known as the other top destination for tech jobs[4] but the reasons cited as to why this is happening do not involve whether or not NCAs are prohibited in Washington. Instead, affordable housing is often considered the biggest draw. The key is: while California ranks next to last in terms of NCA enforcement, Washington ranks quite high at 13, suggesting little evidence of people considering NCA a factor when moving (or at least it is not so compelling as to outweigh other reasons such as cost of living). Looking at the most recent data, The Computing Technology Industry Association's 2019 reported: Florida (despite topping the list of NCA enforceability score) actually appears in second after California in terms of net tech employment job gains and fourth in tech employment overall. As a last step, since some states in America are considered more expensive to live in than others and this could potentially affect the results, I attempted to add in an additional independent variable that will account for the differences in each state's cost of living. The source for this information comes from data released by the U.S Bureau of Economic Analysis (BEA) which compares the relative cost of living in different parts of the country. Their most recent report on Real Personal Income for States and Metropolitan Areas came out last year using 2017 data. To compare costs of living, the BEA utilized Regional Price Parities (RPPs), which measure the differences in price levels across states and metropolitan areas for a given year and are expressed as a percentage of the overall national price level. All items RPPs cover all consumption goods and services, including housing rents. RPP sets the national average cost of goods and services at 100, and a particular region's RPP will show how the cost of living in that region compares with the average. For example, if New York's RPP is 115.8 , this means the state is about 15.8% more expensive to live in than the national average.

VI.   Results

First we estimate the 4 equations (2), (4), (5), (6) using the full sample. Given the aforementioned set of 9 dependent variables, we are running here a total of 36 models. Table 2 highlights only the coefficient of interest on NCA score. A table of these regressions' sample sizes can be found in Appendix Table A4.

The effects of NCA enforcement remain consistently negative for Log of Total Compensation, Base Salary and Bonus. The coefficients' magnitudes and standard errors tend to get smaller as we control for more fixed effects. Overall, the majority of our coefficients using log dependent variables indicate a negative relationship between NCA score and the amount of compensation. This points towards premium and punitive constraints being substitutes. If that is the case, NCA enforceability (a punitive constraint) causes use of fewer premium constraints. Consistent with Balasubramanian et al. (2019) and Johnson et al. (2020)'s findings, we observe lower wages in states that more effectively enforce NCAs. If NCAs restrict subsequent worker mobility, it will reduce their pay. On top of rarely being negotiated, NCAs can prevent workers from earning what they could in a competitive market (Starr 2019). Furman and Krueger (2016) also cited NCAs as a factor contributing to monopsony power, which dampens labor turnover and reduces overall economic dynamism.

There is also mild to moderate evidence to claim that, not only does total compensation shrink overall due to substitution, the proportion of pay comprised by bonus also decreases. This is further confirmed as one looks back at the log regressions and sees that on average, given the same experience, gender, firm, title and job specialty, switching from a state with zero enforcement (North Dakota) to highest enforcement (Florida) will reduce a tech worker's annual compensation by about 17%, base salary by 15%, stock by 30% and bonus by 20%. This translates to bonus decreasing at a faster rate than the total sum does (20%>17%). If this is indeed the case, then we can show mathematically that percentage of the component (bonus) compared to the sum must decrease as a result of being subject to a stricter enforcement regime. One can think of it as the exact opposite idea of when the total market for a product or service grows, then a company that is growing its market share, i.e. its percentage of a market's total sales, will definitely be growing its revenues at a faster rate than the average of all companies. Given a negative coefficient on percentage of bonus to the sum, even if total annual pay stays exactly the same, the proportion of that compensation that is incentive-based is decreasing, meaning that firms do not feel like they need to further incentivize workers to exert effort.

Comparing to other high-skilled workers, Lavetti et al. (2019) applied their theoretical model on physician compensation to advocate for the role of incentive pay in counteracting the potential decline in bargaining power associated with NCAs. Nevertheless, our results here suggest that productivity-based incentives or bonuses have fallen short of achieving such a goal for technology workers by dwindling away at a rate even quicker than total earnings itself. We do not have much consistent evidence with either the base salary or the equity component to make any definitive claim, however. Adding division fixed effects did not alter by much the direction and magnitude of the results which we did find of significant value in previous parts. That bolsters our empirical strategy since it is not just that different parts of the country are different. Even when I just compare one state to its nearby neighbors, there is still an effect while also taking into account the fact that we are talking about only one firm with the firm fixed effect.

As mentioned before, by recognizing that California started out on the NCA spectrum with such an extreme score value while at the same time attracting the majority of tech workers could induce bias, I examine the model using data without Californians. I use equation (6) (a fully saturated model with all of the controls mentioned above). The dependent variables of interest are still the logs of the different monetary compensations and the percentages of each component to the total annual salary. Table 3 shows these results using data outside of California. The sample size has reduced, yet we still find evidence of significant coefficients. This indicates strongly that there exists a meaningful relationship between the constraints we are studying (premium and punitive constraints). Furthermore, the degree of estimated effects is even bigger than when California was included. Considering that California also has an extremely low enforcement score, I infer that the state attracted a wide mix of talent levels, most likely including a lot of the newly minted graduates that are at the bottom of the pay scale. In the compensation regressions for workers outside of California, both total salary and base pay still exhibit a significant substitution relationship with our measure of punitive constraints (while including division effects). For tech employees outside California, moving from a state with zero NCA enforcement to the most enforceable state can cost them about 33% of total earnings and 24% in base salary. Compared to the previous table, the magnitude of effects here is quite large, even without leverage from Californian workers. Besides the diminished sample size, this can also happen due to the fact that, while California may host many high earning workers, it is also home to a lot more of those that earn relatively lower than average of the remaining states. Note as well how contribution of non-base pay to the total sum is significantly reduced when NCAs are more enforceable for states excluding California. It is also dwindling at a rate faster than that of stock's percentage (whose coefficient is also somewhat significant). The only other component that makes up non-base pay is bonus and given that percentage of stock is not decreasing as fast as stock-plus-bonus combined, the percentage of bonus, therefore, must have decreased as well. Thus, although the negative coefficient on SCORE in the percentage of bonus regression does not attach statistical significance, it is unlikely this incentive-based compensation was effectively bundled with NCAs to counteract its impacts of reducing workers' bargaining power in the technology sector. A ban on NCAs then could result in firms increasing pay and making bonuses a larger share of pay. As shown in Table 4, when we allow control for the differences in states' relative cost of living (or how expensive it is to live in each state), the coefficient on SCORE is still negative for all 9 regressions except for the one using percentage of base salary to total compensation as a dependent variable. However, this means that increased NCA enforceability affects percentage of non-base salary to total compensation negatively. Even though the estimated size of effect is smaller than before, the SCORE coefficient is significant at the 5% level where log of total compensation, log of base salary and percentage of non-base salary were used. The size of reduction estimated for percentage of bonus, stock, and stock-plus-bonus combined is 3%, 5%, and 8% respectively.

Lastly, I attempt to examine whether there is heterogeneity in my results by gender. This is motivated by the fact that women are still underrepresented in tech and they had been, by tradition, more geographically constrained than men (Childers et al. 2019), making them more susceptible to negative effects of NCAs. There is only one woman in our sample who stays in the industry for more than 30 years, whereas 31 men accumulate anywhere from 30 to over 50 years of experience (the woman's mean Total Annual Compensation is also smaller than the mean of those 31 men). Considering this, a binned line plot (Figure 4) was drawn, focusing only on the first 30 years of each gender. An interesting avenue of research then is to look at the split

between 2 genders and see if the effect of NCA policy on pay composition remains the same. Table 5 presents such results, reporting coefficient on SCORE as we run regressions including only one gender at a time, combined with including and excluding California. On average, descriptive statistics show that non-Californian women are the lowest earning group out of the 4, then men out of California third, and men in California take home the most salary. Most of our previous assertions towards substitution for log of Total and Base Salary and percentage of productivity-based incentives still hold as before, with the weakest evidence in the non-Californian females group (although this could just be an econometric artifact due to small cell size). In general, high enforceability levels of NCAs affect overall pay negatively. Females outside California are also the ones who sustain the most impact to earnings if they were to work in a more enforcing state. There is obviously a difference in effects between men and women in that women tend to endure more negative impact, which did not come much as a surprise as the coefficient on FEMALE in our previous regressions using Equation (6) has strong statistical significance attached (for example, the FEMALE coefficients for Equation (6) in the full sample using log of Total and log of Base salary are both negative and significant at the 5% level). This gender gap is bigger when one considers only the workforce outside California. There is also a trend of men seemingly incorporating more equity into their compensation than do women.

VII.   Conclusions

"(Workers) can't reach their true potential without freedom to negotiate for a higher wage with a new company, or to find another job after they've been laid off," said ex-Vice President Joe Biden in a statement as cited in the Reuters News[5]. The Obama administration had previously called on U.S. states to ban agreements which prohibit workers from moving to employers' rivals. To bind employees, there are different human resource practices that can increase the immobility of human capital by raising workers' costs of changing employers (Chadwick and Dabu 2009). While there are financial methods such as offering high salaries that are the opportunity costs employees will forfeit if they depart, NCAs are examples of nonfinancial ones that punish leaving workers and impose on them real costs such as time, energy, money and may be even reputation (Kryscynski and Starr 2019). Focusing purely on the technology industry, I have found evidence to establish a pattern of substitution between a worker's earnings and his residing state's policy on NCAs. Using Kryscynski and Starr (2019)'s terminologies on labor retention, if there are already aggressive contracts (or punitive constraints) that assert employers' ownership of intellectual property and results of training, then firms can utilize that legal system to replace financial benefits (or premium constraints). This means companies have less incentives to offer high salaries or a greater share of the gains when the firm succeeds, knowing workers' bargaining power has been reduced. As a result, a ban on NCA would lead to a more competitive labor market and faster wage growth. This matter can potentially affect people who are as early in their careers as new graduates, thus making it important that students should also be informed of NCA's potential impacts to make good careers decisions.

The substitution relationship that I have found is especially more evident with total and base pay than with non-base values, while also more strongly applied for women than it is for men. An interesting avenue for future research would be to examine whether there is also heterogeneity by experience. For example, one can assess whether the effect of NCA policy on pay composition is any different for people that have only been in the industry for a short time compared to more seasoned workers. Given how firms may pay new hires a lot up front to get them to agree on signing enforceable NCAs before locking them in, and that firms also want to avoid

committing to a high salary rates for the new person, we can test to see how much bigger bonuses are for new workers than for workers who have been at the company for a while, in low versus high enforcing states.

Applying this paper's discussions to the case of Silicon Valley's high-velocity market where enforcement of NCAs is virtually impossible, an employer that needs motivations to invest in employee training can incorporate elements that provide incentives for employees to stay such as financial ones. Besides high rates of employment mobility, some of the region's many characteristics also feature flexible compensation, including stocks. Using thorough breakdown of compensation data collected in an online public source, I assessed the effect of varying degrees of NCA enforceability at different states on representation of each pay component in the overall pay structure. My results show that there is moderate evidence to claim that the percentage of incentive-based pay in the compensation make-up is diminished as NCAs are more enforceable. From the firm's perspective, there is less incentive to use these as retention device when there is already effective legal means. This means productivity-based payments given to workers have failed to counteract the potential decline in bargaining power associated with NCAs, a phenomenon that was discussed as one of Lavetti et al. (2019)'s hypotheses during their study on share-based compensation.

VIII.   References

Abowd, J. M., F. Kramarz, and D. N. Margolis. "High Wage Workers and High Wage Firms." *Econometrica* 67, no. 2 (1999): 251–333. https://doi.org/10.3386/w4917.

Acemoglu, Daron. "Investments in General and Specific Skills." Lecture notes at Massachusetts Institute of Technology, Cambridge, MA, November 29 and December 1, 2011. Accessed January 20, 2020. https://economics.mit.edu/files/7408.

Ali, Zulfiqar, Hongyi Sun, and Murad Ali. "The Impact of Managerial and Adaptive Capabilities to Stimulate Organizational Innovation in SMEs: A Complementary PLS–SEM Approach." *Sustainability* 9, no. 12 (2017): 2157. https://doi.org/10.3390/su9122157.

Baird, Lloyd, and Ilan Meshoulam. "Managing Two Fits of Strategic Human Resource Management." *The Academy of Management Review* 13, no. 1 (1988): 116. https://doi.org/10.2307/258359.

Balasubramanian, Natarajan, Jin Woo Chang, Mariko Sakakibara, Jagadeesh Sivadasan, and Evan Starr. "Locked In? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers." *US Census Bureau Center for Economic Studies Paper No. CES-WP-17-09; Ross School of Business Paper No. 1339* (December 5, 2019). http://dx.doi.org/10.2139/ssrn.2905782.

Bishara, Norman. "Fifty Ways to Leave Your Employer: Relative Enforcement of Covenants Not to Compete, Trends, and Implications for Employee Mobility Policy." *SSRN Electronic Journal*, 2011. https://doi.org/10.2139/ssrn.2014277.

Chadwick, Clint. "Theoretic Insights on the Nature of Performance Synergies in Human Resource Systems: Toward Greater Precision." *Human Resource Management Review* 20, no. 2 (2010): 85–101. https://doi.org/10.1016/j.hrmr.2009.06.001.

Chadwick, Clint, and Adina Dabu. "Human Resources, Human Resource Management, and the Competitive Advantage of Firms: Toward a More Comprehensive Model of Causal Linkages." *Organization Science* 20, no. 1 (2009): 253–72. https://doi.org/10.1287/orsc.1080.0375.

Childers, Chandra, Ariane Hegewisch, Tanima Ahmed, and Amy Burnett. *Geographic Mobility, Gender, and the Future of Work.* Washington, DC: Cross Institute for Women's Policy Research, 2019. Accessed January 22, 2020. https://iwpr.org/wp-content/uploads/2019/12/C487_Geographic-Mobility-FOW.pdf

Coff, R. W. "Human Assets and Management Dilemmas: Coping with Hazards on the Road to Resource-Based Theory." *The Academy of Management Review* 22, no. 2 (March 1997): 374-402. https://doi.org/ 10.5465/AMR.1997.9707154063.

Cyberstates 2019: *The Definitive Guide to the U.S. Tech Industry and Tech Workforce.* The Computing Technology Industry Association (CompTIA), March 2019. Accessed January 22, 2020. https://www.cyberstates.org/pdf/CompTIA_Cyberstates_2019.pdf

Delery, J. E., and D. H. Doty. "Modes Of Theorizing In Strategic Human Resource Management: Tests Of Universalistic, Contingency, And Configurations. Performance Predictions." *Academy of Management Journal* 39, no. 4 (January 1996): 802–35. https://doi.org/10.2307/256713.

Fallick, Bruce, Charles A. Fleischman, and James B. Rebitzer. *Job-Hopping in Silicon Valley: Some Evidence Concerning the Micro-Foundations of a High Technology Cluster*. Washington (D.C.): Federal reserve board, 2005.

Furman, Jason and Alan B. Krueger, "Why Aren't Americans Getting Raises? Blame the Monopsony," Op-ed *The Wall Street Journal*, November 3 2016.

Garmaise, Mark J. "Ties That Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment." *Journal of Law, Economics, & Organization* 27, no. 2 (2011): 376-425. Accessed January 11, 2020. www.jstor.org/stable/41261726.

Gilson, Ronald J. "The Legal Infrastructure of High Technology Industrial Districts: Silicon Valley, Route 128, and Covenants Not to Compete." *SSRN Electronic Journal*, 1998. https://doi.org/10.2139/ssrn.124508.

Hausman, N. and Kurt Lavetti. "Physician Concentration and Negotiated Prices: Evidence from State Law Changes." Working Paper, 2019.

Hyde, Alan. *Working in Silicon Valley Economic and Legal Analysis of a High-Velocity Labor Market*. Armonk (N.Y.): M.E. Sharpe, 2003.

Johnson, Hans, Marisol Cuellar Mejia and Sarah Bohn. *Will California Run Out of College Graduates?* California: Public Policy Institute of California, 2015. Accessed January 22, 2020. https://www.ppic.org/content/pubs/report/R_1015HJR.pdf

Johnson, Matthew S., Kurt Lavetti, and Michael Lipsitz. "The Labor Market Effects of Legal Restrictions on Worker Mobility." Working Paper, 2020.

Khair, Qura-tul-aain, and Muhammad Mohtsham Saeed. "Different Ways of Synergistic Effects of Human Resource Management (HRM) Practices on Organizational Performance: A Method of 2 2 =5." *African Journal of Business Management* 5, no. 21 (2011): 8610–16. https://doi.org/10.5897/ajbm10.683.

Kryscynski, David, and Evan Starr. "Examining Practice Adoption: When Firms Adopt Value Creation and Value Protection Practices." Working Paper, 2019.

Lavetti, Kurt, Carol Simon, and William D. White. "The Impacts of Restricting Mobility of Skilled Service Workers: Evidence from Physicians." *Journal of Human Resources*, July 2019. https://doi.org/10.3368/jhr.55.3.0617-8840R5.

Marx, Matt. "The Firm Strikes Back." *American Sociological Review* 76, no. 5 (2011): 695–712. https://doi.org/10.1177/0003122411414822.

Reiche, Sebastian B. "The Configuration of Employee Retention Practices in Multinational Corporations' Foreign Subsidiaries." *International Business Review* 17, no. 6 (2008): 676–87. https://doi.org/10.1016/j.ibusrev.2008.09.004.

Rubin, Paul H., and Peter Shedd. "Human Capital and Covenants Not to Compete." *The Journal of Legal Studies* 10, no. 1 (1981): 93–110. https://doi.org/10.1086/467672.

Starr, Evan. "Consider This: Training, Wages, and the Enforceability of Covenants Not to Compete." Forthcoming at *Industrial and Labor Relations Review* (May 2018). http://dx.doi.org/10.2139/ssrn.2556669.

Starr, Evan, James J Prescott, and Norman Bishara. "Noncompetes in the US Labor Force." Working Paper, 2017.

United States Census Bureau, Geography Division. "Census Regions and Divisions of the United States". https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf (Retrieved January 20, 2020).

U.S. Department of the Treasury, Office of Economic Policy. "Non-compete Contracts: Economic Effects and Policy Implications." Washington, D.C. (March 2016). https://www.treasury.gov/resource-center/economic-policy/Documents/UST%20Non-competes%20Report.pdf (accessed March 16, 2020).

U.S. Senate Committee on Small Business and Entrepreneurship. *Written Testimony for the Senate Committee on Small Business and Entrepreneurship Hearing on "Noncompete Agreements and American Workers"*. by Evan Starr, 2019. https://www.sbc.senate.gov/public/_cache/files/0/5/057b45f1-32f4-4df6-acb8-3f045b29385a/93BA66135DAAE345899743196B5653C5.starr-testimony.pdf (accessed January 16, 2020).

Wei, Li-Qun. "Strategic human resource management: determinants of fit." *Research and Practice in Human Resource Management* 14, no. 2 (2006). Gale Academic Onefile (accessed January 16, 2020).

Williamson, O.E. "Transaction-Cost Economics: The Governance of Contractual Relations," *The Journal of Law and Economics* 22, no. 2 (October 1979): 233-261. https://doi.org/10.1086/466942.

IX. Tables and Figures

Table 1. Summary Statistics

Variable	Mean	Minimum	Maximum	Standard deviation
Base Salary	153,909	5,000	1,050,000	55,154
Bonus	24,098	0	1,000,000	37,172
Stock Grant Value	63,865	0	4,822,000	131,528
Total Yearly Compensation	239,848	10,000	5,000,000	180,227

Table 2. Estimates of Standardized Score's Coefficients Using Full Sample Size

Dependent Variable	Model Specifications			
	(2)	(4)	(5)	(6)
Log of Total Compensation	-0.374**	-0.188***	-0.172***	-0.101***
	(0.145)	(0.066)	(0.057)	(0.035)
Log of Base Salary	-0.243***	-0.154***	-0.152***	-0.117***
	(0.058)	(0.042)	(0.037)	(0.028)
Log of Bonus	-0.993***	-0.246***	-0.202***	-0.277*
	(0.221)	(0.052)	(0.062)	(0.146)
Log of Stock	-2.408	-0.356	-0.309	0.017
	(1.85)	(0.254)	(0.222)	(0.132)
Log of Non-Base Salary	-1.119	-0.265	-0.254	-0.028
	(0.857)	(0.164)	(0.164)	(0.086)
Percentage of Base to Total Compensation	0.084	0.015	0.008	-0.013
	(0.059)	(0.018)	(0.016)	(0.008)
Percentage of Bonus to Total Compensation	0.005	-0.006***	-0.003*	-0.005*
	(0.005)	(0.002)	(0.001)	(0.003)
Percentage of Stock to Total Compensation	-0.089	-0.009	-0.006	0.018**
	(0.055)	(0.018)	(0.015)	(0.007)
Percentage of Non-Base to Total Compensation	-0.084	-0.015	-0.008	0.013
	(0.059)	(0.018)	(0.016)	(0.008)
Company Fixed Effect	No	Yes	Yes	Yes
Job Title Fixed Effect	No	No	Yes	Yes
Specialty Fixed Effect	No	No	Yes	Yes
Division Fixed Effect	No	No	No	Yes

Note: Standard errors in parentheses and clustered by state. * $p<0.1$, ** $p<0.05$, *** $p<0.01$
This table reports results on 36 models and only highlights NCA Score's coefficients.

Table 3. Regression Results Excluding California

	Log of Total Compensation	Log of Base Salary	Log of Bonus	Log of Stock	Log of Non-Base Salary	Percentage of Base Salary	Percentage of Bonus	Percentage of Stock	Percentage of Non-Base Salary
SCORE	-0.332**	-0.243**	-0.518	-2.229*	-1.190	0.0865***	-0.0274	-0.0592*	-0.0865***
	(0.137)	(0.119)	(0.742)	(1.251)	(0.717)	(0.0289)	(0.0173)	(0.0326)	(0.0289)
YEARS OFEXP	0.0327***	0.0208***	0.00397	0.0719***	0.0569***	-0.00667***	0.000556	0.00612***	0.00667***
	(0.00109)	(0.00144)	(0.0177)	(0.0104)	(0.00529)	(0.000631)	(0.000332)	(0.000920)	(0.000631)
YEARSAT COMPAN Y	0.00478**	0.00645***	-0.128***	0.0291	0.00485	0.00117*	-0.00325***	0.00207**	-0.00117*
	(0.00187)	(0.00158)	(0.0392)	(0.0272)	(0.0156)	(0.000641)	(0.000795)	(0.000883)	(0.000641)
FEMALE	-0.0352*	-0.0285***	0.312	-0.236	-0.0897*	-0.00209	0.0102*	-0.00810	0.00209
	(0.0202)	(0.00963)	(0.191)	(0.157)	(0.0519)	(0.00287)	(0.00541)	(0.00490)	(0.00287)
Constant	12.20***	11.87***	8.628***	9.514***	10.78***	0.703***	0.122***	0.175***	0.297***
	(0.103)	(0.0910)	(0.658)	(0.981)	(0.549)	(0.0213)	(0.0140)	(0.0257)	(0.0213)
N	4067	3611	3611	3611	3611	3611	3611	3611	3611
Adj. R^2	0.650	0.583	0.409	0.700	0.613	0.603	0.247	0.539	0.603

Note: Standard errors in parentheses and clustered by state. * p<0.1, ** p<0.05, *** p<0.01

Include company, job title, area of focus and division effects.

Table 4. Regression Results Adding Control for Cost of Living

	Log of Total Compensation	Log of Base Salary	Log of Bonus	Log of Stock	Log of Non-Base Salary	Percentage of Base Salary	Percentage of Bonus	Percentage of Stock	Percentage of Non-Base Salary
SCORE	-0.273** (0.106)	-0.198** (0.0953)	-0.638 (0.741)	-2.035 (1.290)	-1.196* (0.699)	0.0760** (0.0281)	-0.0261 (0.0175)	-0.0499 (0.0312)	-0.0760** (0.0281)
YEARS OFEXP	0.0327*** (0.00108)	0.0207*** (0.00142)	0.00402 (0.0177)	0.0718*** (0.0104)	0.0569*** (0.00528)	-0.00667*** (0.000636)	0.000555 (0.000331)	0.00611*** (0.000925)	0.00667*** (0.000636)
YEARSAT COMPANY	0.00487*** (0.00178)	0.00659*** (0.00145)	-0.128*** (0.0389)	0.0296 (0.0276)	0.00484 (0.0156)	0.00114* (0.000632)	-0.00324*** (0.000798)	0.00210** (0.000859)	-0.00114* (0.000632)
FEMALE	-0.0359* (0.0202)	-0.0291*** (0.00942)	0.314 (0.192)	-0.238 (0.158)	-0.0897* (0.0516)	-0.00196 (0.00289)	0.0102* (0.00540)	-0.00821 (0.00497)	0.00196 (0.00289)
RPP	0.00983*** (0.00197)	0.00654*** (0.00154)	-0.0174 (0.0112)	0.0280 (0.0185)	-0.000835 (0.0117)	-0.00152** (0.000573)	0.000184 (0.000212)	0.00133** (0.000630)	0.00152** (0.000573)
Constant	11.11*** (0.232)	11.14*** (0.176)	10.56*** (1.119)	6.403** (2.429)	10.87*** (1.249)	0.872*** (0.0722)	0.101*** (0.0268)	0.0269 (0.0807)	0.128* (0.0722)
N	4067	3611	3611	3611	3611	3611	3611	3611	3611
Adj. R^2	0.653	0.587	0.409	0.701	0.613	0.604	0.247	0.540	0.604

Note: Standard errors in parentheses and clustered by state. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Include company, job title, area of focus and division effects. California Excluded.

Table 5. Heterogeneity by Gender

Dependent Variable	Equation (6) Model			
	Female, full sample	Male, full sample	Female, no California	Male, no California
Log of Total Compensation	-0.170***	-0.090**	-0.856	-0.323**
	(0.037)	(0.036)	(0.638)	(0.133)
Log of Base Salary	-0.166***	-0.108***	-0.858**	-0.270**
	(0.024)	(0.029)	(0.305)	(0.117)
Log of Bonus	0.708	-0.367*	-10.471*	-0.746
	(0.418)	(0.186)	(5.955)	(0.861)
Log of Stock	-1.158***	0.141	-7.202	-1.643
	(0.235)	(0.156)	(6.830)	(1.107)
Log of Non-Base Salary	-0.546**	0.022	-11.269*	-0.837
	(0.221)	(0.110)	(5.873)	(0.732)
Percentage of Base to Total	0.010	-0.016*	0.446**	0.064**
Compensation	(0.009)	(0.008)	(0.204)	(0.031)
Percentage of Bonus to Total	0.027***	-0.008**	-.0146*	-0.036**
Compensation	(0.005)	(0.003)	(0.069)	(0.017)
Percentage of Stock to Total	-0.038***	0.024***	-0.300	-0.028
Compensation	(0.007)	(0.007)	(0.198)	(0.034)
Percentage of Non-Base to	-0.010	0.016*	-0.446**	-0.064**
Total Compensation	(0.009)	(0.008)	(0.204)	(0.031)
Company Fixed Effect	Yes	Yes	Yes	Yes
Job Title Fixed Effect	Yes	Yes	Yes	Yes
Specialty Fixed Effect	Yes	Yes	Yes	Yes
Division Fixed Effect	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses and clustered by state. * $p<0.1$, ** $p<0.05$, *** $p<0.01$
This table reports results on 36 models and only highlights NCA Score's coefficients.
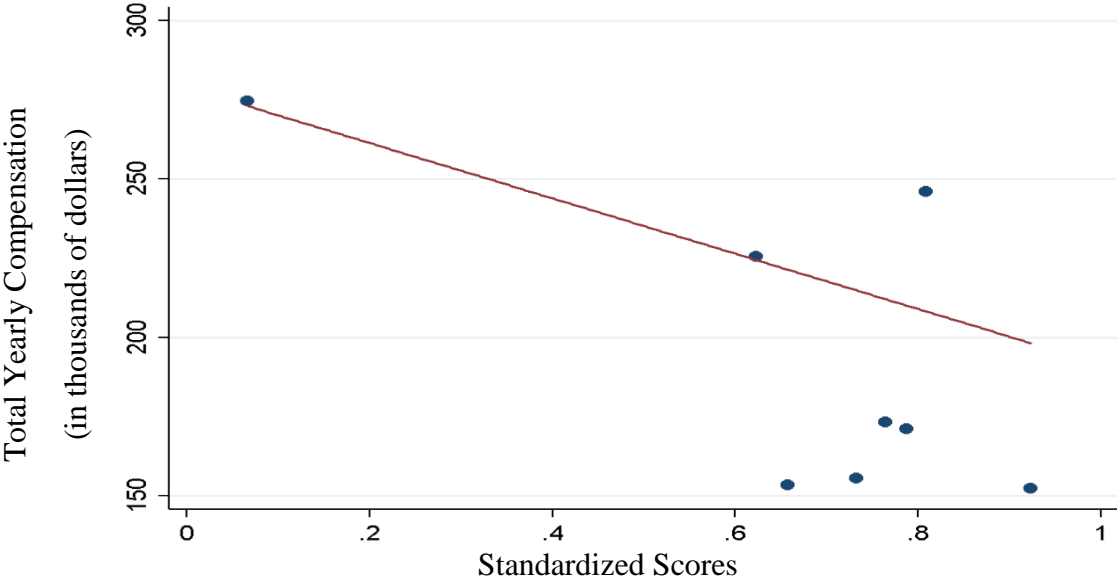
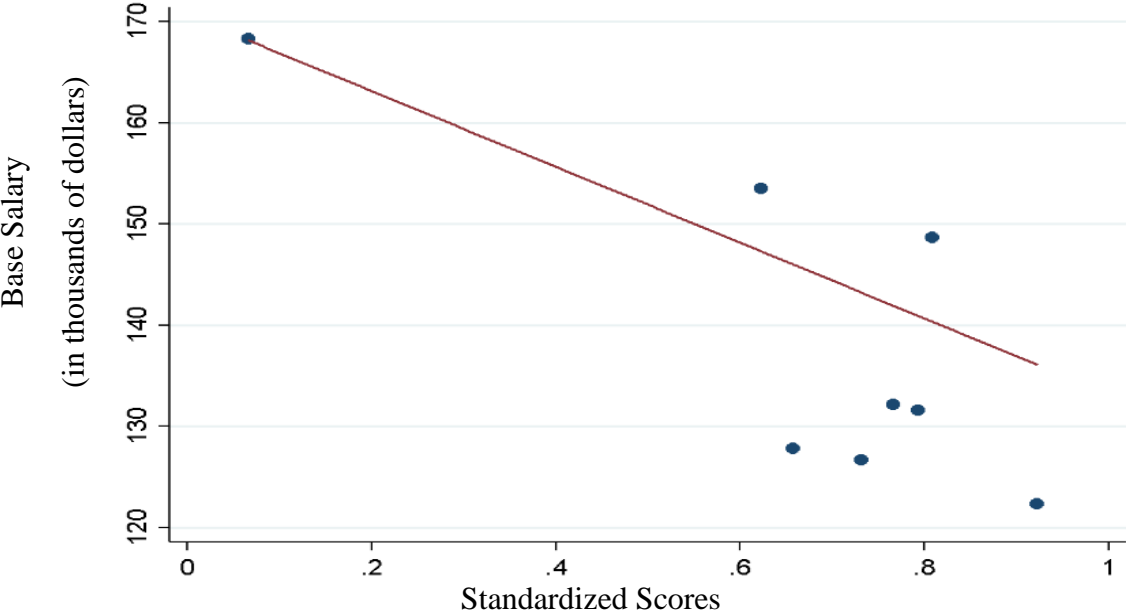Figure 1. Total Yearly Compensation against NCA Scores

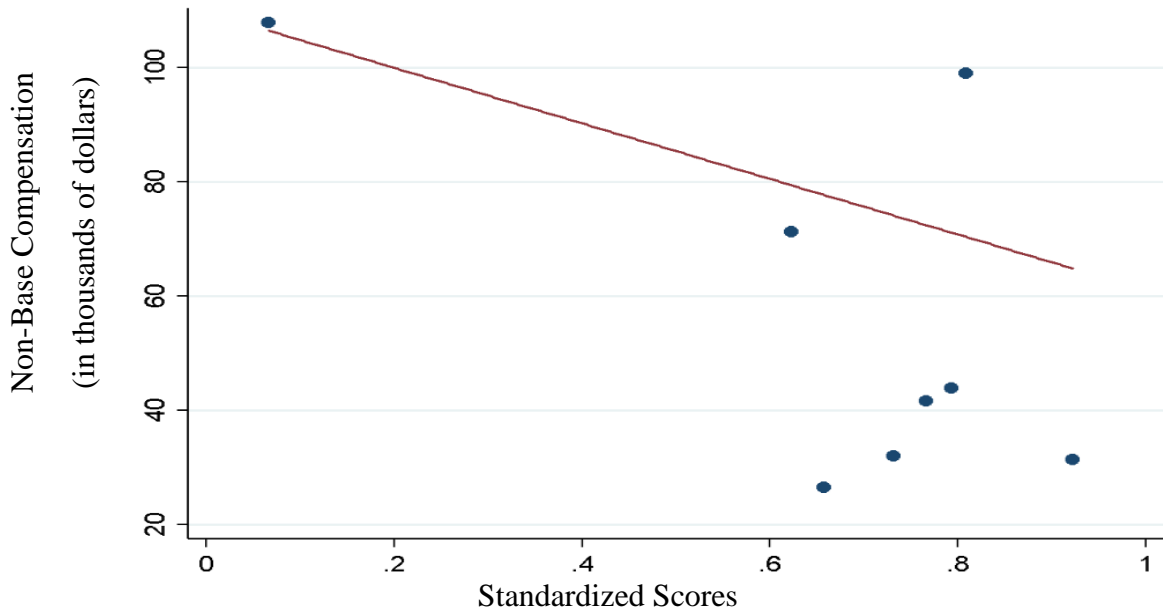

Figure 2. Base Salary against NCA Scores

Figure 3. Non-Base Compensation (Bonus and Stock) against NCA Scores
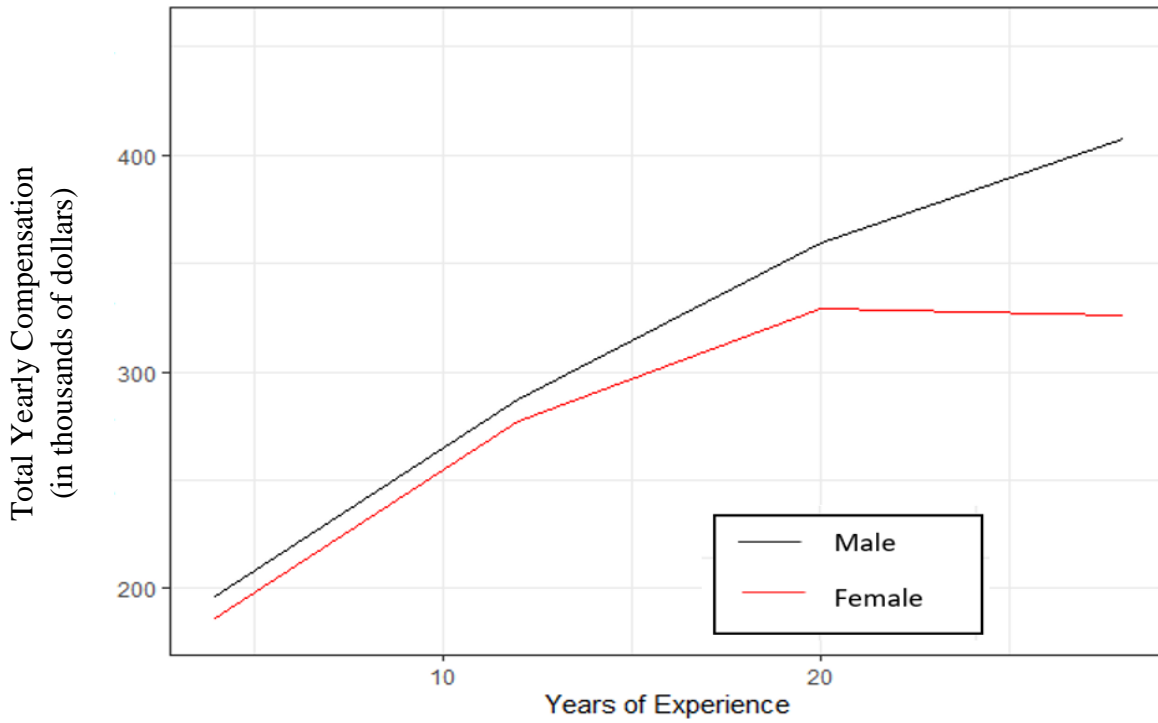

Figure 4. Total Yearly Compensation by Gender during the First 30 Years

X.   Appendix

Table A1. Bishara's Enforcement Scores

State Name	Averaged Total Score
Alabama	373
Alaska	241
Arizona	316
Arkansas	230
California	31
Colorado	360
Connecticut	435
Delaware	360
District of Columbia	310
Florida	470
Georgia	285
Hawaii	358
Idaho	429
Illinois	430
Indiana	370
Iowa	425
Kansas	455
Kentucky	415
Louisiana	380
Maine	370
Maryland	379
Massachusetts	375
Michigan	379
Minnesota	340
Mississippi	360
Missouri	425
Montana	259
Nebraska	281
Nevada	342
New Hampshire	361
New Jersey	425
New Mexico	409
New York	295
North Carolina	335
North Dakota	0
Ohio	355
Oklahoma	248
Oregon	361
Pennsylvania	365
Rhode Island	314
South Carolina	310
South Dakota	410
Tennessee	373
Texas	350
Utah	428
Vermont	379
Virginia	310
Washington	380
West Virginia	281
Wisconsin	300
Wyoming	360

Table A2. Nine divisions defined by the United States Census Bureau

Division	States
1	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont
2	New Jersey, New York, and Pennsylvania
3	Illinois, Indiana, Michigan, Ohio, and Wisconsin
4	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota
5	Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, and West Virginia
6	Alabama, Kentucky, Mississippi, and Tennessee
7	Arkansas, Louisiana, Oklahoma, and Texas
8	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming
9	Alaska, California, Hawaii, Oregon, and Washington

Table A3. Tests for Potential Correlation with States' NCA Enforcement Scores

	Coefficient	Standard Error
Innovation Ranking	-0.016	0.024
Productivity in Tech Ranking	-0.006	0.024

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A4. Sample Sizes of Regressions Used in Table 2

Dependent Variable	Model Specifications			
	(2)	(4)	(5)	(6)
Log of Total Compensation	9,522	8,687	7,980	7,980
Log of Base Salary	8,412	7,708	7,063	7,063
Log of Bonus	8,412	7,708	7,063	7,063
Log of Stock	8,412	7,708	7,063	7,063
Log of Non-Base Salary	8,412	7,708	7,063	7,063
Percentage of Base to Total Compensation	8,412	7,708	7,063	7,063
Percentage of Bonus to Total Compensation	8,412	7,708	7,063	7,063
Percentage of Stock to Total Compensation	8,412	7,708	7,063	7,063
Percentage of Non-Base to Total Compensation	8,412	7,708	7,063	7,063
Company Fixed Effect	No	Yes	Yes	Yes
Job Title Fixed Effect	No	No	Yes	Yes
Specialty Fixed Effect	No	No	Yes	Yes
Division Fixed Effect	No	No	No	Yes

XI.   Endnotes

1. Torry, Harriet. "Interns' Job Prospects Constrained by Noncompete Agreements." *The Wall Street Journal*, June 29, 2019.

2. Leswing, Kif. "Here's How Big Tech Companies Like Google and Facebook Set Salaries for Software Engineers." *CNBC*, June 15, 2019.

3. Hagan, Shelly and Wei Lu. "California Is the Most Innovative Economy in America." *Bloomberg,* April 16, 2019.

4. Lipton, Josh. "Silicon Valley techies are fleeing to Seattle." *CNBC*, March 20, 2017.

5. Wiessner, Daniel. "White House Urges Ban on Non-Compete Agreements for Many Workers." *Reuters*, October 25, 2016.