Training and Job Separation in Imperfect Labor Markets: The Case of Non-Compete Agreements

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Abstract

Non-compete agreements are provisions within employment contracts that prevent workers from joining competing firms. They are prevalent in the US workforce, with 38% of workers having signed such clauses at some point in their careers. Despite their vast usage, there is limited research on the incentives for workers and firms to use non-compete agreements. We show that non-compete agreements can create one market failure – inefficient lack of job separation – while mitigating a separate market failure – inefficient provision of industry-specific investment by firms. The model yields the predictions that (i) non-compete agreements are more likely to be used in industries where employer training is more "general" and (ii) non-compete signers have longer job tenures, higher wages, and receive more firm-provided investment relative to similar workers without non-compete agreements. Using newly-released panel data on the usage of non-compete agreements from the NLSY97, we test the model's predictions. Consistent with the theory, we find that non-compete signers are more concentrated in knowledge-intensive industries, remain with their employers for 3 more months than individuals without such agreements, and receive a 7% wage premium for signing a non-compete agreement. Non-compete signers do not experience higher wage growth or measures of employer provided investment.

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1 Introduction

The theory that labor markets are perfectly competitive has come under scrutiny in recent decades (e.g. Card 2022; Naidu and Posner 2021). Non-compete agreements – provisions within employment contracts that prevent workers from joining competing firms – are often discussed as a factor that provides firms with wage-setting power. According to survey estimates, they are prevalent in the US workforce, with 38% of workers having signed non-compete agreements at some point in their careers (Starr, Prescott, and Bishara 2021). Despite their vast usage, there remains much controversy surrounding whether non-compete agreements enhance the efficiency of the labor market.[1]

Proponents of non-compete agreements argue that they increase worker retention and encourage firms to develop the industry-specific skills of their workforce.[2] The productivity gains from such investment may be shared with labor, thus increasing wage growth in the long-run. Opponents state that non-compete agreements lock workers into their jobs, creating mobility frictions that prevent workers from joining firms where they would be more productive.[3] Reduced labor market competition due to non-compete agreements may allow firms to retain labor at lower wages, thus decreasing wage growth.

In this paper, we develop a theoretical model to show how non-compete agreements can create one market failure – inefficient lack of job separation – while mitigating a separate market failure – inefficient provision of (non-contractible) industry-specific investment by firms.[4] The worker

[1]This controversy is recently reflected by the Federal Trade Commission's proposal to ban the enforcement of non-compete agreements in the United States ("FTC Proposes Rule to Ban Noncompete Clauses, Which Hurt Workers and Harm Competition" 2023).

[2]In perfectly competitive labor markets, firms do not profit from providing general (or, for that matter, industry-specific) skills (Becker 1962). If they were to increase the productivity of the worker by a given amount (say δ), they would need to increase compensation by δ in order to retain the worker.

[3]Critics also cite that non-compete agreements may deter business formation, as new businesses would struggle to poach workers bound under such an agreement (i.e. Aghion and Bolton 1987, Jeffers 2019). In addition, firms may impose non-compete agreements upon workers who are not aware the provision is part of the employment contract, thereby allowing firms to exploit labor in the form of worse wages and working conditions.

[4]When investments are non-contractible, variations in investment by one party cannot be measured or priced by the courts. The modelling choice to make investment non-contractible follows a long literature studying how contracts may be designed to encourage investment and resolve the hold-up problem (i.e. Grossman and Hart 1986; Che and Hausch 1999). If investment were contractible, the parties would choose the efficient level, with or without a non-compete agreement.

and firm's choice then of whether to include a non-compete agreement balances these two considerations. The parties sign a non-compete agreement if the productivity gains from the firm's investment outweigh the expected costs of inefficient separation.

While existing literature has documented that non-compete agreements may encourage firm-provided investments (i.e. Meccheri 2009), we contribute by showing that non-compete agreements also prevent an efficient (ex-post) matching between workers and firms. Many economists adopt the principle that contract renegotiation is costless, in which case firms may be willing to release workers from non-compete agreements in exchange for an appropriately sized buyout payment (i.e. Shi 2023; Posner, Triantis, and Triantis 2004). When job separation is socially efficient, the third party would be willing to fund such a buyout payment, thus restoring the efficient matching between workers and firms.[5] In contrast, we assume that workers have private information about their outside options and that this information cannot be credibly communicated to firms, as in Hashimoto (1981). The large transaction costs associated with contracting on the worker's outside option makes renegotiation prohibitively costly, preventing efficient matches between workers and third parties from becoming realized.[6]

We believe the theory has an intuitive appeal in understanding the costs and benefits generated by mobility frictions, though we are not the first to show that contracting affects ex-ante investment decisions or the efficiency of ex-post separation decisions. When workers can be released from non-compete agreements, Shi (2023) illustrates that contracting parties may sign a non-compete agreement in order to extract buyout payments from future employers. This rent extraction is socially excessive but encourages firm-provided investment. Grossman and Hart (1986) show

[5]Workers who are not wealth constrained may also independently fund the buyout payment. More generally, when matching with the third party is socially efficient and the parties are not wealth constrained, the buyout payment offered to the incumbent firm may be split arbitrarily between the worker and the third party. This is nothing other than a restatement of the Coase Theorem.

[6]To further elaborate, the firm cannot verify the terms of the worker's outside offer since it is private information to the worker. As such, the worker cannot command a higher wage by claiming to have a superior outside offer because the firm will assume such claims are inflated. Therefore, the worker may be poached by third parties that value the worker less than the incumbent firm. More generally, if the parties do not have the ability to renegotiate the initial contract, there may be inefficient separations as well as inefficient lack of job separation. Our modelling decision to prevent parties from renegotiating the contract follows the suggestion of Hart and Moore (2007), who urge scholars to develop models with ex-post inefficiencies.

that contracting parties may allocate authority rights at the contracting phase to encourage the provision of non-contractible investments by the more productive party. MacLeod and Malcomson (1993) demonstrate that fixed-wage contracts that require the mutual consent of both parties for renegotiation encourage firms to provide the efficient level of relationship-specific investments. Acemoglu and Pischke (1999) show that when mobility frictions increase in a worker's skill, firms are incentivized to provide general training. Pakes and Nitzan (1983) develop a model where a flat first period wage and a state-contingent second period wage can yield efficient ex-ante and ex-post matching, though they do not consider how contracting affects investment incentives.

We add to the literature by showing that mobility frictions such as those generated by non-compete agreements can be a double-edged sword – they encourage firms to provide industry-specific investment while preventing efficient job separation. Our model thus sheds insight on how the structure of contracts within workplaces influences the employer's incentives to provide transferable skills (e.g. Acemoglu and Pischke 1999; Lynch and Black 1998). Our results further imply that blanket bans on the enforcement of non-compete agreements may have short-term gains as workers flow into jobs in which they are more productive, but have long-term consequences in terms of a less-skilled workforce.

Our model predicts that non-compete signers have longer job tenures, higher wages, are more likely to receive employer-provided training, and are concentrated in industries where skills are easily transferable. These predictions can be tested using newly released panel data on non-compete usage from the National Longitudinal Survey of Youth (NLSY97). The survey follows a variety of outcomes for individuals who were teenagers in 1997, though the first year the survey tracks non-compete status is 2017, when the sample is aged 32 - 38.[7] A strength of the NLSY97 is that it tracks the usage of non-compete agreements and detailed characteristics of non-compete signers among a representative sample of prime-aged workers. This feature stands in contrast to much of the related literature that analyzes the effects of non-compete agreements in narrowly defined labor markets, such as in particular occupations, industries, or firms (i.e. Shi 2023; Lavetti,

[7] Of the 5084 individuals who responded to the questionnaire, 731 (14%) reported having a non-compete agreement in their contract.

Simon, and White 2020).[8]

Several descriptive statistics support the model's predictions. Individuals who sign non-compete agreements are 3 percentage points more likely to receive employer-paid training than those who do not sign such agreements, and the difference is statistically significant at the 10 percent level.[9] Non-compete signers are more likely to work in knowledge-intensive industries such Professional Services than in industries requiring more routine work, such as Construction.[10] They also have longer tenures with their employers. The respondents who indicated signing a non-compete agreement in 2017 had a mean job tenure of 5.2 years, compared to 4.9 years among those who do not have non-compete agreements. Despite the fact that non-compete signers receive more on the job training, they do not experience higher wage growth. Between the 2017 and 2019 survey rounds, nominal wages of non-compete signers and non-signers both increased by 18%. The difference is not statistically significant at conventional levels, which provides suggestive evidence that in this context, employers do not share the rents generated from increased investment with labor.

These differences may not reflect causal impacts if non-compete signers have different (observed or unobserved) characteristics than those who do not sign such agreements. Indeed, the fact that non-compete signers are more concentrated in high-wage and knowledge-intensive industries suggests that this critique may be valid. We attempt to deal with this issue in several ways. First, in cross-sectional regressions, we control for observable characteristics that may be correlated with non-compete usage and wages, such as age, tenure, potential experience, gender, and industry composition. This exercise reaffirms the conclusion that non-compete agreements raise wages but not wage growth. Second, we adopt an identification strategy where we compare the

[8]An exception is Rothstein and Starr (2021), who study non-compete usage in the 2017 cross-section using the NLSY97. They document that individuals who sign non-compete agreements have higher wages. Since their analysis restricts to the cross-section, they cannot study the relationship between non-compete agreement and wage growth. Their cross-sectional analysis also prohibits the use of causal inference techniques that rely upon panel data. Shi (2023) uses panel data to examine the relationship between non-compete usage and firm-provided investments among executives, but her data on investments is at the firm level (as opposed to the individual level). This limitation prevents an analysis of whether individuals who sign non-compete agreements receive more firm-provided investment.

[9]This result is consistent with Starr (2019), who finds that increased state-level enforcement of non-compete agreement raises firm sponsored training.

[10]25% of respondents working in Professional Services reported having a non-compete agreement, while 11% of respondents in Construction reported having a non-compete agreement.

trajectory of outcomes for those who signed non-compete agreements to those who never signed non-compete agreements over the sample period. This comparison nets out any time-invariant and un-observable characteristics that may differ between those with and without non-compete agreements. After showing that the parallel trends assumption may be satisfied when the outcome is log(wages), we find that non-compete agreements raise wages by 7% within one year and 13% within five years. Furthermore, the signing of a non-compete agreement lowers the incidence of a job separation by at least 9 p.p within one year, though the magnitude of the coefficient dissipates over time. Corroborating the previous analysis, we find no systematic relationship between the signing of a non-compete agreement and wage growth. However, unlike in the previous exercises, we reject the hypothesis that non-compete agreements raise measures of employer-provided training.

The paper proceeds as follows. Section 2 lays out the theoretical framework. Section 3 discusses data sources and Section 4 tests the model's predictions. Section 5 concludes.

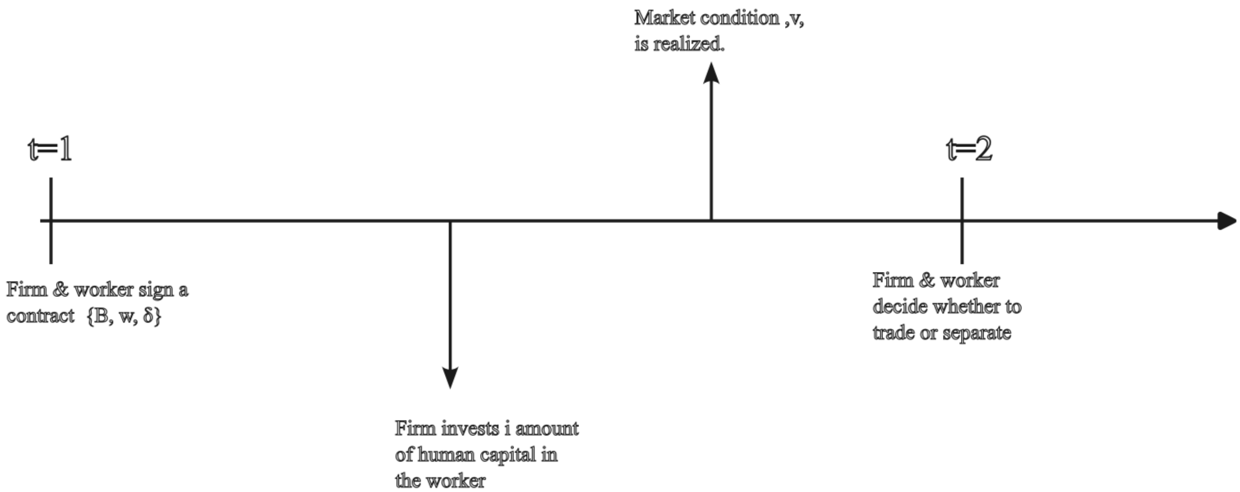
2 Theoretical Framework

2.1 The Model

Our model features two periods. In the first period ("ex-ante"), a single worker W and firm F choose a contract, which consists of a wage w and may include a non-compete agreement $\delta \in \{0,1\}$.[11] The non-compete agreement prevents W from moving to poaching firms θ within the same industry as F. Between the first and second period, F sinks non-contractible industry-specific investments i with associated cost $i^2/2$ that raise W's productivity within F by r, should trade between the parties occur. At the time the investment is made, it is uncertain how much F's investment raises W's productivity if separation occurs. At the beginning of period 2, overall

[11] The parties also have the option of making side payments to each other at the contracting stage. Let B denote the side-payment made by W to F at the contracting stage. We assume that $B \geq 0$. This assumption can be justified on several grounds. One reason is that it is unrealistic for workers to post bonds to employers (i.e. Baker, Gibbons, and Murphy 1994). Another is that the firm may be unable to commit to a rising wage profile or deferred benefits. Note that the wage may depend on whether the non-compete agreement is included in the contract.

Figure 1: Timeline of the Model



market conditions $v \sim logNormal(\mu, \sigma^2)$ are revealed and a poaching firm $\theta \in \{0,1\}$ makes an offer to W. With probability q, the poaching firm is in the same industry as the original firm ($\theta = 1$) and values the worker at $v + \rho \times i$. With remaining probability, the poaching firm is outside of the original firm's industry ($\theta = 0$) and values the worker at v.[12] Observe that F's investment raises W's productivity among poaching firms only when $\theta = 1$. We assume the labor market is competitive ex-post, so the poaching firm makes an offer equal to its valuation.[13] As in Hashimoto (1981), we further assume that the poaching firm's offer is private information to the worker. After the worker receives his outside offer, the parties can trade at the contractual terms or separate.[14] To simplify matters, we suppose that the poaching firm is always an industry competitor ($q = 1$).

The incentives for parties to use a non-compete agreement will depend on a comparison between the internal return on investment r and the external return on investment ρ.[15] In our model, r and ρ can take arbitrary values, so we do not constrain firm-provided investment to be purely specific or industry-specific. We choose to be agnostic about the exact values of these parameters

[12] Note that if $q = 1$ and $\rho = r$, the investment is completely general.

[13] A similar assumption is made in Spier and Whinston (1995), pg 186-188

[14] Since trade is voluntary, W can quit or F can fire. The firm's payoff from trade (net of investment) is $ri - w$, while the worker's is w. The firm's payoff from separation is 0. The worker's payoff from separation is $\bar{w} = v + \big(\theta(1-\delta)\big)\rho \times i$. F fires the worker if $w > ri$, and W quits if $w < \bar{w}$. Since workers are not allowed to make transfer payments to the firm in the initial period, in equilibrium, the wage will always be less than the value of the worker's output.

[15] When investment is purely specific, $\rho = 0$, and when investment is purely industry-specific, $r = \rho$.

since they may differ across industries. For example, the internal return on investment may be large relative to the external return on investment among individuals in the Education, Health, and Social Services industry, where average job tenures are long. In contrast, the external returns on investment may be large relative to the internal return on investment in Professional and Related Services, where job-hopping between firms in the same industry is more common.[16]

The model approximates the ideal of a perfectly-competitive labor market in all but one exception – the worker has private information on the outside option which cannot credibly be communicated to the incumbent firm. Otherwise, we highlight that the poaching firm makes an offer equal to its valuation of the worker. This assumption can be justified in a setting where there are many homogeneous firms who each simultaneously bid for the worker's services.[17] In addition, the firm must offer a contract that meets or exceeds the utility value of the worker's outside option in order for the worker to accept. In perfectly competitive labor markets, this value equals the worker's utility from accepting a job at one of many other homogeneous firms.

First, consider what happens if the parties do not include a non-compete agreement in the contract. At the investment stage, the firm chooses investment to equate marginal cost and expected marginal benefits. It earns a return of r when trade occurs, but does not earn a private return when separation occurs even though such investment would raise W's productivity by ρ. Anticipating this, F underinvests, which is the well-known hold-up problem.

One solution to the hold-up problem is for W and F to write a contract that reduces the chance that job separation occurs (i.e. Autor 2003; MacLeod and Malcomson 1993). A binding non-compete agreement fits this bill, as W is less likely to quit when $\delta = 1$ than when $\delta = 0$, holding all else equal. The non-compete agreement thus encourages F to invest more but prevents W from joining the industry competitor, even when such separation is socially efficient.[18]

[16]As of January 2022, the median job tenure for workers in Professional and Business Services is 3.4 years, while that for Education and Social Services is 4 years: https://www.bls.gov/news.release/pdf/tenure.pdf

[17]The poaching firm and the incumbent firm may place different weights on the worker's human capital, which contributes to different valuations for the worker's services (e.g. Lazear 2009).

[18]This occurs when $ri \geq w \geq v$ and $\rho \times i > 0$

2.2 Benchmark Outcomes

To more formally describe how firms under-invest relative to the socially optimal quantity without a non-compete agreement, we first characterize the planner's allocation. The social planner invests and allocates workers to firms efficiently. In the final period, the social planner executes trade between the worker-firm match if the social surplus from trade exceeds that of separation. This condition occurs when $S^T \geq S^{NT}$, where $S^T = ri_s - c(i_s)$ and $S^{NT} = v - c(i_s) + \rho i_s$. Thus it is efficient to trade if $v \leq (r-\rho)i_s$. Denote $p_s := \Phi(\frac{ln((r-\rho)i_s)-\mu}{\sigma})$ as the probability that trading is efficient from the perspective of the initial period. The efficient investment level is solved by the following equation:

$$i_s^* = \text{argmax } E(S) = -c(i_s) + (ri_s) \cdot p_s + [v + \rho i_s] \cdot (1 - p_s) \tag{1}$$

Proposition 1: If $r < \rho$, separation is always efficient and the efficient investment level is $i_s^* = \rho$. If $r > \rho$, the efficient investment level is $i_s^* = rp_s + \rho(1-p_s)$. The probability of separation is not equal to 0, and the efficient investment level increases with r and ρ.

Proof: If $r < \rho$, $P\big(v \leq (r-\rho)i_s\big) = 0$, so separation is always efficient. Solving $i_s^* = \text{argmax } E(S) = -c(i_s) + v + \rho i_s$ we have $i_s^* = \rho$. The efficient level of investment increases with ρ. See the appendix for case when $r > \rho$.

Corollary 1: As investment becomes more specific, the planner's probability of separation declines.

Proof: $\partial p_s / \partial (r-\rho) > 0$.

When the external return on investment is larger than the internal return on investment, poaching firms always have a higher valuation than the incumbent firm. As a result, separation is always efficient ex-post. On the other hand, when the internal return on investment is larger than the external return on investment, trading is not necessarily efficient ex-post. When market conditions are sufficiently strong, the planner assigns the worker to the poaching firm; otherwise, the planner maintains the match between the incumbent firm and worker.

2.2.1 A Simple Example

We use a simple example with exogenous investments to illustrate how non-compete agreements create "job-lock", or inefficient lack of job separation. We still use the same setup described in Subsection 2.1, but we assume that the investment level, i, is a fixed parameter. Hence the only actions are for the firm to offer a contract in period 1 and for the parties to make separation decisions in period 2. For a given wage, we compare ex-post separation decisions when non-compete agreements are and are not used.

When the worker and firm use a non-compete agreement, the worker will remain with the firm so long as the wage is less than or equal to the outside option, or when $w \leq v$. The region where trade will occur is given by the shaded region in Figure 2. The scenarios where trade occurs in a competitive equilibrium differs from the scenarios where trade occurs under an efficient allocation between workers and firms. To see this point, Figure 2 also visualizes the efficient trading rule presented in Section 2.2. When $r > \rho$, trade is efficient whenever $v \leq (r-\rho)i$, depicted by the region below the dashed line and above the x-axis. When $\rho > r$, trading is never efficient, as the poaching firm always has a higher valuation than the incumbent firm. We observe that two types of (allocative) inefficiencies occur with a non-compete agreement. First, there are inefficient separations: there are scenarios where trade is efficient but separation occurs. This case is represented by the region below the dashed line and above the shaded area. Second, there are cases where separation is efficient but where it does not occur. This case is depicted by i) The shaded region when $r-\rho < 0$ and ii) the shaded region above the dashed line when $r-\rho > 0$.

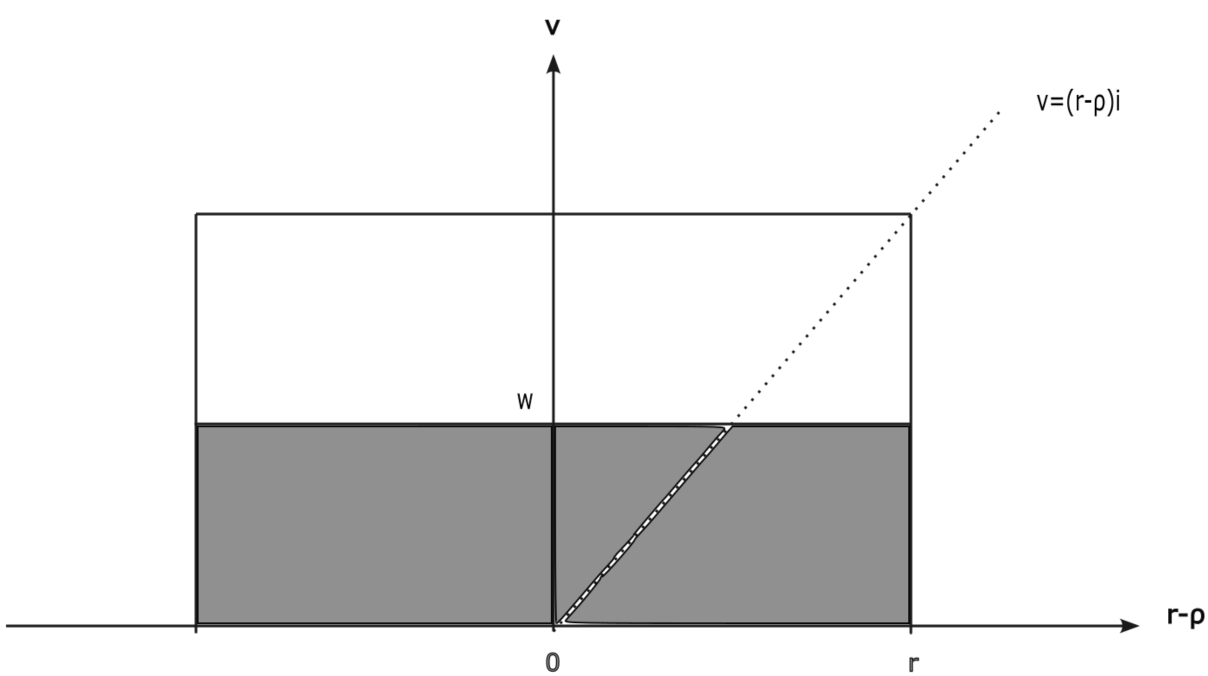
Under the assumptions of our model, all efficient separations are realized when a non-compete agreement is excluded from the contract. When the worker's outside option exceeds the firm's valuation, that is when $v+\rho \cdot i > ri$, the worker always quits. To see why this is the case, observe that the firm will never offer a contract where it earns negative profits ex-post.[19] Hence $w \leq ri < v+\rho \cdot i$,

[19]This conclusion is a consequence of our assumption that workers cannot make transfer payments to firms in the initial period (i.e. $B \geq 0$)

so the worker will quit when separation is efficient. However, for any given wage, inefficient quits are more likely to occur without a non-compete agreement than with a non-compete agreement.[20]

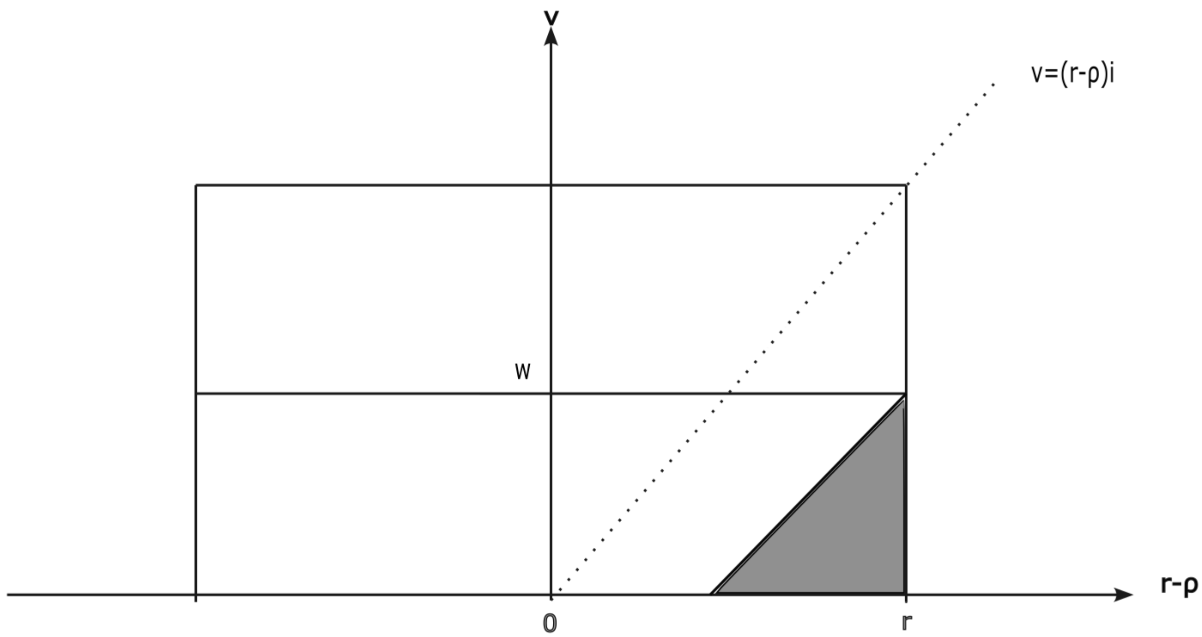
This example illustrates that inefficient separation decisions occur both with and without a non-compete agreement. Since the initial wage cannot be renegotiated ex-post, there are instances where the worker finds it profitable to quit even though the incumbent firm has the highest valuation. There are inefficient quits without a non-compete agreement, but all efficient separations are achieved. The reason is that the wage never exceeds the incumbent firm's valuation, so the worker will quit when a poaching firm has the highest valuation. In the presence of a non-compete agreement, there are scenarios where efficient job separation is not realized, as the agreement may block the worker from moving to a poaching firm with a higher valuation. However, there are fewer inefficient quits with a non-compete agreement than without a non-compete agreement.

Figure 2: Separation Decisions with a Non-Compete Agreement



[20]Observe that $Pr(v > w|v \leq (r-\rho)i_s) < Pr(v+\rho \cdot i > w|v \leq (r-\rho)i_s)$

Figure 3: Separation Decisions without a Non-Compete Agreement



2.3 General Results

We solve for the Subgame Perfect Nash Equilibrium. At $t = 2$, the worker quits if the outside option is higher than the wage they receive in the last period. The outside option is v if a non-compete is signed and $v + \rho i$ if a non-compete is not signed:

$$W : \text{Stay} \iff w_\delta \geq v + \rho i_\delta (1 - \delta) \tag{2}$$

Since v is not known before investment, we denote $p_\delta = \Phi(\frac{\ln(w_\delta - \rho i_\delta (1-\delta)) - \mu}{\sigma})$ as the ex-ante probability of the match persisting. Between $t = 1$ and when market conditions are revealed, the firm makes human capital investments. We can solve for the firm's profit maximizing level of investment (conditional on the parameters of the contract) with the following equation.

$$\widetilde{i_\delta} = \text{argmax } E(\pi^F_\delta) = -c(i_\delta) - B_\delta + p_\delta (r i_\delta - w_\delta) \tag{3}$$

In the first period, the firm offers a contract that specifies a wage, bonus, and may contain a non-compete agreement. It makes this choice taking into account the participation constraints of the worker and firm, as well as by anticipating decisions later in the game. Since the firm offers the contract, the worker's participation constraint is binding, so that $E(\pi^W) = \mu_0$.[21]

$$w^*_\delta, B^*_\delta = \text{argmax } E(\pi^F_\delta) \text{ s.t. } E(\pi^F_\delta) \geq 0,\ E(\pi^W_\delta) = \mu_0, \text{ and } B_\delta \geq 0 \tag{4}$$

Proposition 2: When a non-compete agreement is not signed, the firm will under-invest relative to the socially optimal quantity ($i^*_0 \leq i^*_s$). When $r \geq \rho$, there is always inefficient separation ($0 < p^*_0 \leq p^*_s < 1$). When $\rho > r$, there is efficient turnover without a non-compete agreement.

Proof: See Appendix.

Proposition 3: There is more employer-provided investment ($i^*_0 \leq i^*_1$), higher cross-sectional wages ($w^*_0 \leq w^*_1$) and less turnover ($0 < p^*_0 \leq p^*_1 < 1$) with a non-compete agreement than without a non-compete agreement.

Proof: See Appendix.

Proposition 4: When $r < \rho$, a non-compete agreement is always used. When $r > \rho$, it is ambiguous whether the parties use a non-compete agreement.

Proof: See Appendix.

2.4 Discussion

Propositions 1-4 constitute our main theoretical results and provide a framework to guide our empirical analysis. First, we characterize the efficient allocation, which consists of an investment level and an ex-post mapping between workers and firms. We show that the efficient level of investment increases as we raise the return on investment. Next, we show that absent a non-compete agreement, there is under-investment relative to the socially optimal quantity. This well-known hold-up

[21] Once we solve for the wage and bonus levels, we can plug into $\tilde{i_\delta}$ to arrive at i^*_δ.

problem occurs in our context because there are inefficient separations without a non-compete agreement. Our main theoretical result is that a non-compete agreement lowers turnover and raises firm-provided investment, thereby mitigating the hold-up problem. If the external returns on investment are large relative to the internal returns on investment, the probability of a job separation is large without a non-compete agreement. The firm thus has an incentive to use a non-compete agreement to raise investment and profits. In the remaining cases, the firm uses a non-compete agreement if the gains from a higher expected return on investment outweigh the costs from higher wages.

In our model, non-compete signers earn higher wages because firms must compensate workers for their reduced option value of job search. We show in Appendix Section 6.4 that workers receive compensation for signing a non-compete agreement in the form of higher wages rather than an up-front bonus. All else equal, firms prefer to provide compensation with higher wages, since higher wages reduce the probability of a job separation.[22]

Our empirical results do suggest that non-compete signers earn higher cross-sectional wages, which is consistent with our theoretical prediction.[23] However, the predicted effect of non-compete agreements on wages may be negative under modified modelling assumptions. In our Monopsony Appendix, we extend our baseline model so that a single firm offers a contract to hetereogenous workers with varying reservation utilities. As in Hashimoto (1981), these reservation utilities are private information to workers. We show that when the firm uses a non-compete agreement, employment is less than socially efficient and that wages may be lower than without a non-compete agreement.[24]

[22] Both higher wages and up-front bonus payments raise the worker's utility, but up-front bonus payments do not affect the worker's decision to quit or stay ex-post.

[23] In our fully saturated model that includes controls for tenure, age, gender, potential experience, and industry, we find that non-compete agreements are associated with 16% higher wages in the 2017 cross-section and 20% higher wages in the 2019 cross-section.

[24] By lowering wages, the monopsonistic firm attracts fewer workers but earns more profits per worker. Without a non-compete agreement, the firm has employment less than the socially efficient level and earns positive (ex-post) profits per worker (Proposition A1). A non-compete agreement may result in even lower wages and employment than without a non-compete agreement if the gains in profit-per-worker exceed the losses in employment. However, whether this occurs depend on the exact parameters of our theoretical model.

3 Data

We use data from the National Longitudinal Survey of Youth 1997 (NLSY97) to understand the characteristics of non-compete signers and analyze the effects of such agreements on job tenure, employer-provided training, wages, and wage growth. This dataset is a nationally representative panel that tracks the outcomes of individuals aged 12-16 in 1997. The NLSY97 starts measuring whether non-compete agreements are used within employment contracts starting in 2017, when survey respondents are between ages 32-36. In 2017, all working respondents are asked whether they have a non-compete agreement. In 2019, the following survey round, only individuals who obtained a new job between survey rounds are asked about their non-compete status.

Among 5081 respondents who replied to the non-compete questionnaire, 713 (14%) indicated that they had a non-compete agreement. More than 90% of affirmative respondents reported being "Very Confident" in their answer. We obtain similar rates of non-compete usage when we look at responses in the 2019 survey round: among the 1716 individuals who obtained new jobs between survey rounds, 233 respondents (14%) reported having a non-compete agreement (Table A2).[25] There is substantial heterogeneity in non-compete usage across the 17 (two-digit) industries considered. Table 1 shows that among industries with more than 100 respondents, non-compete agreements are most commonly used in Professional and Related Services (26%) and least commonly used in Public Administration (8%).

We are interested in the relationships between non-compete agreements and various labor market outcomes. We measure job tenure in years and job separation as an indicator variable for whether an individual separated jobs between survey years.[26] Employer-provided training is measured in several ways; we consider whether the employer directly provides training as well as whether the employer pays for training. As a default, we report statistics pertaining to whether an individual has ever previously received employer-provided training in a given job. We observe the hourly wages of respondents in all survey years between 2011 and 2019, allowing us to assess

[25] While individuals may hold multiple jobs, we restrict all analysis to an individual's primary job.

[26] The sample period runs from 2011 to 2019, and the survey years are 2011, 2013, 2015, 2017, and 2019.

whether non-compete signers have higher or lower wage growth relative to individuals who do not sign such agreements. This data also allows us to inquire whether non-compete signers have higher wages in the cross-section, even after controlling for observable characteristics.

4 Results

We observe that non-compete signers earn 5.69 dollars more per hour, or 25% more, than individuals without non-compete agreements in the 2017 cross-section.[27] To probe the incentives for parties in an employment relationship to use non-compete agreements, we chart usage of these agreements by industry (Table 1). Consistent with the developed theory, we observe greater prevalence of non-compete agreements in higher-wage industries where knowledge may be easily transferable. On average, 14% of respondents have non-compete agreements, but in Professional Services and Information and Communication (the two industries with the highest non-compete prevalence), this number is 26% and 23% respectively. In contrast, 8% of respondents report signing non-compete agreements in Public Administration and Education, Health, and Social Services, the two industries with the lowest prevalence.[28]

Individuals who report signing a non-compete agreement in 2017 have starting wages of $23 per hour, a four dollar premium relative to those who do not report signing a non-compete agreement in 2017. The estimated cross-sectional wage premium for signing a non-compete agreement declines as we add control variables (Tables A3, A5), which implies that differences in starting wages is partly attributable to the fact that, on average, non-compete signers have characteristics that are positively associated with employment outcomes. Table 2 provides further evidence that supports this claim. In the 2017 cross-section, we find that non-compete signers stay with their employers for 4 more months and are 5 percentage points less likely to have a job separation than their counterparts, which is consistent with our theory. They also have more formal education, as

[27] In fact, we can say something stronger about the wage distribution: for both men and women, the wage distribution among non-compete signers is a rightward shift of that among non-signers (Figure 4)

[28] Agriculture, Forestry, and Fisheries, and Active Duty Military have lower usage, but fewer than 35 respondents fall under these categories.

reflected by the fact that non-compete signers are 10 percentage points more likely to have a bachelors degree or higher. Employers also provide more training to those who sign a non-compete agreement: 29% of respondents with a non-compete reported having received some type of training, relative to 27% for those without a non-compete agreement. We observe similar differentials when we consider employer-run or employer-paid training as the outcome variable.[29]

Table 3 examines training differentials among high and low non-compete usage industries. Our theory predicts that in industries where training is more "general," non-compete agreements are used more frequently and are more likely to encourage firm-provided investments. We observe training differentials in high-usage industries but not in low-usage industries, which is also consistent with the theory. In high-usage industries, non-compete signers are 6 percentage points more likely to receive employer-paid training, a difference that is statistically significant at the 1% level. By contrast, the training differential is indistinguishable from 0 in low-usage industries.[30] Similar patterns emerge when considering employer-run training or receipt of any training as an outcome. Interestingly, the training premium we observe in high-usage industries does not carry over to high-usage occupations or high-wage earners (Table 3, Rows 3-6).[31]

Despite the fact that non-compete signers receive more firm-provided training, they do not experience higher wage growth. Table 2 shows that between the 2017 and 2019 survey years, both non-compete signers and non-signers experienced an 18% increase in wages. This result is not an artifact of the sample period considered. When we look at the 2015 to 2017 sample period, we again observe similar patterns of wage growth between the two groups. Figure 5 further corroborates this result by showing that there is no relationship between industry-level usage of

[29]Though we note the 2 p.p. differential for training run by the employer is not statistically significant at the 10% level. In contrast to the firm-level investment measures in Shi (2023), we measure training at the individual-level. Our sample of workers is also approximately 10 years younger than her sample of executives (mean age of 34 in our study versus mean age of 45 in Shi (2023)). Nevertheless, we arrive at similar differences in job tenure among those with and without non-compete agreements (0.30 years in our sample versus 0.10 years among the sample of executives).

[30]In unreported results, we probe even further by examining training differentials by industry. While we observe a training premium associated with non-compete agreements in the overwhelming majority of industries, limited sample sizes within industry cells prevent us from making further conclusions about the particular industries where non-compete agreements raise firm-provided investments.

[31]We speculate this result is due to the fact that non-compete agreements restrict mobility within industry and not within occupation. However, further research on why we observe this pattern is warranted.

non-compete agreements and wage growth between 2017 and 2019.

The qualitative relationships between non-compete agreements, wages, and wage growth are robust to several identification strategies.[32] In Tables A3 - A6, we estimate the coefficients from the following equation via Ordinary Least Squares:

$$Y_i = \beta_0 + \beta_1 * NC_i + \beta_2 * X_i + \varepsilon_i \tag{5}$$

These estimates represent causal effects if non-compete signers and non-signers have similar potential outcomes, conditional on the covariates included in the regression specification. We consider wages in 2019, wage growth between 2017 and 2019, wages in 2017, and the incidence of employer-paid training as the dependent variables.[33] Table A3 shows that the estimated impact of non-compete agreements on wages declines as we add control variables. In the no-controls specification in Column 1, the wage premium associated with signing a non-compete agreement is 28%. In the fully saturated model of Column 6, which has industry fixed effects and controls for age, tenure, gender, and potential experience, the estimated wage premium falls to 16%. We observe a similar pattern when considering cross-sectional wages in 2017 as the outcome variable (Table A5). The causal estimates of non-compete agreements on wage growth and employer-provided investment on the other hand are insensitive to the inclusion of covariates. Across Cols 1-6 in Tables A4 and A6, we find a precisely-estimated zero effect of non-compete agreements on the outcomes considered.[34]

Even in the fully saturated model, however, we cannot rule out the possibility that there are omitted variables correlated with non-compete usage and labor market outcomes of interest. Our developed theory suggests that individuals who sign non-compete agreements have high external returns on firm provided investment.[35] If these individuals also have higher ability, for exam-

[32]The effects of non-compete agreements on employer-provided investment depends on the identification strategy used.

[33]When analyzing the relationships between non-compete agreements and cross sectional wages, we prefer using the 2019 cross-section since all respondents are relatively new job holders.

[34]By 'precisely estimated zero', we mean that the boundaries of the 95% confidence interval are small relative to the dependent variable mean.

[35]The "external return on firm provided investment" corresponds to the parameter ρ in the theoretical model.

ple, then our estimated coefficients will be upward biased. To address this concern, we adopt a research design where we compare the trajectory of outcomes of individuals who signed non-compete agreements to those that never signed non-compete agreements over the sample period. If those who sign non-compete agreements have higher time-invariant un-observable characteristics, then this comparison nets out such differences. More formally, we estimate the parameters of the following Event Study regression using data from 2011 to 2019 and the method provided by Callaway and Sant'Anna (2021):

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k \in \{-6,-4,0,2,4,6\}} \beta^k d_{i,t-k} + \varepsilon_{it}, \text{where} \tag{6}$$

$d_{it} = 1\{e_i = t\}$ is an event indicator that takes the value of 1 in the first year of treatment.

In other words, d_{it} equals one in the first year an individual starts a job with a reported non-compete agreement.[36] Here our identifying assumption is that each cohort of non-compete signers and the set of individuals who never sign non-compete agreements between 2011 and 2019 have similar trends in potential outcomes. A cohort contains all the individuals who first signed non-compete agreements in a given year. The Callaway and Sant'Anna (2021) method to estimate the event study coefficients proceeds in a two-step fashion. In the first step, the effect of the treatment is estimated for each cohort and year. In the second step, the cohort-specific estimates are aggregated (using the authors' doubly-robust method) across cohorts so as to generate a single estimate for each relative time period. Standard errors are clustered at the individual level, and the excluded period is the one before the treatment year, which is relative period -2.

We are interested in $\hat{\beta}^k, k \geq 0$, which represents the causal effect of signing a non-compete agreement if the identifying assumption holds. Table 5 provides suggestive evidence that the parallel trends assumption may hold when the outcome is Log(Wages). Between relative periods -6

[36]Non-compete status is first reported in 2017. Thus, we make the assumption that if an individual has a non-compete in 2017 and is in the same job prior to 2017, then the individual also has a non-compete prior to 2017.

and -2, Log(Wages) evolves similarly for non-compete signers and non-signers. When we look at other outcomes in Table 5, we see different trends among signers and non-signers. For example, members of the treatment group appear to have faster wage growth prior to non-compete adoption than those in the control group. Similarly, rates of job separation are growing faster in the treatment group than in the control group prior to adoption. If these trends were to continue into the post-treatment period, then this pattern implies that the estimates corresponding to relative period 0 and beyond are under-estimates.

We find that non-compete agreements raise wages within 1 year both in specifications without control variables and with controls variables for tenure, sex, and educational attainment. Without controls, the signing of a non-compete agreement is associated with a 7% increase in wages, while with controls the number rises to 20%. These results corroborate the finding from Table A3, which performs a cross-sectional analysis using data from 2019 to find that the signing of a non-compete agreement is tied with a 16.1% wage increase. The wage gains from signing a non-compete agreement persist: within 5 years, the wage premium from signing a non-compete agreement is 13%, a finding that is robust to the inclusion of control variables.

Table 5 also shows the impact of non-compete agreements on wage growth. The coefficients corresponding to the post-treatment periods in Column 3 are statistically indistinguishable from 0, with the exception of the fourth relative period. The null effects on wage growth in the Event Study specification supports the descriptive results in Table 4, which shows identical wage growth between 2017 and 2019 among individuals who did and did not report signing non-compete agreements in 2017. Somewhat surprisingly, the event study coefficients posit that non-compete agreements have no impact on the incidence of employer-provided investment. This result runs contrary to the theoretical expectation that non-compete agreements mitigate the hold-up problem, thereby *increasing* employer-provided investments. These results can be rationalized several ways. The first is that the true effect of non-compete agreements on employer-provided investment is zero, and we accurately capture this fact in the event study estimates. The second is that non-compete agreements actually raise employer provided investments, but in ways that are difficult to measure.

Distinguishing between the two theories is an interesting question that we leave to future research.

To probe whether non-compete agreements generate rents that are later shared with labor, we are motivated to analyze wage growth patterns by non-compete *and* job separation status. If such rent sharing occurs, we should observe higher wage growth among non-compete signers who are job stayers over the sample period, relative to job stayers over the same period without non-compete agreements. Our identifying assumption is that absent a non-compete agreement, non-compete signers who remain in their jobs would experience similar wage growth as those who do not sign non-compete agreements and remain in their jobs.

We do not observe evidence of such rent-sharing in Figure 6. Among respondents who remain with their main employer between 2013 and 2019, wage growth is similar among those with and without a non-compete agreement. Interestingly, this pattern even holds among respondents who experience a job separation over the sample period. When we look at wage trajectories by high and low income status in Table 4, we arrive at similar conclusions. Among both high and low income earners, the differential in wage growth is less than 4 percentage points and not statistically significant.[37] Articles in the popular press have often claimed that non-compete agreements are exploitative for low-income workers.[38] When we zoom into the wage patterns for low-income workers in Appendix Figure A3, we observe generally similar patterns as in the overall sample: non-compete signers have higher cross-sectional wages but experience similar wage growth as non-signers. The result that non-compete agreements are associated with higher wages is consistent with Gopal (2023), who finds higher wages under stricter regimes of non-compete enforcement.

5 Conclusion

Economists have long been interested in the factors that promote human capital development. Schooling is often considered as an important determinant of an individual's productivity, but there

[37] Low (high) income workers are defined to be those earning below (above) median wages in the sample.

[38] See for example this article about non-compete agreements in the fast-food industry: https://www.nytimes.com/2014/10/15/upshot/when-the-guy-making-your-sandwich-has-a-noncompete-clause.html

are many skills that can only be learned on the job. The market for employer-provided training, however, suffers a well-known failure: employers do not have an incentive to provide transferable skills if they later need to compensate workers for their increased productivity.

In this paper, we consider the incentives for workers and firms to use non-compete agreements and empirically study their effects on various labor market outcomes. We show that non-compete agreements are used if the gains from transferable skills provided by firms outweigh the expected costs of job-lock. While we view this trade-off between efficient investment and job-separation as intuitive, the model departs from the existing theoretical literature by allowing for ex-post inefficiencies. That is to say, non-compete agreements may prevent workers from moving to firms where they are more productive.

Using newly released panel data on non-compete usage among a representative sample of workers, we test the model's predictions. Non-compete agreements lower job separation rates, raise cross-sectional wages, and are more likely to be used in industries where training is easily transferable. The impacts of non-compete agreements on employer provided investment depend on the choice of sample and statistical methodology. We find no relationship between non-compete agreements and wage growth, suggesting that any rents generated from non-compete agreements are not shared with labor in the short-run.

Our empirical analysis departs from existing literature in several ways. We directly examine the effect of non-compete agreements, as opposed to a large body of work that studies the impacts of non-compete regulation (i.e. Gopal (2023)). By using a moderately large and representative sample, we have been able to study the effects of non-compete agreements on the broader workforce, unlike previous studies that focus on particular occupations, industries, or firms. Our results are thus more likely to generalize to broader segments of the economy relative to existing literature.

Although our analysis provides a better understanding of the usage and impacts of non-compete agreements, future research can address some of the limitations of this study. Our data-set first measures usage of non-compete agreements in 2017 and concludes in 2019, so our panel is relatively short. A panel that tracks individuals across a longer horizon would allows us to determine the longer-run impacts of non-compete agreements. In addition, non-compete agreements may be bundled with other post-employment restrictions, such as non-disclosure agreements and no-solicitation agreements. If such bundling is a common occurrence (i.e. Balasubramanian et al. 2022), then our results identify the joint effects of non-compete agreements and other post-employment restrictions. Nevertheless, this study contributes to the literature by illustrating the incentives for parties to use non-compete agreements and directly analyzing the effects of such agreements on a broad sample.

6 Appendix

6.1 Proposition 1

When $r > \rho$, we solve for the efficient investment level as follows:

$i_s^* = \text{argmax } E(S) = -c(i_s) + p_s \cdot ri_s + (1 - p_s)\rho i_s + (1 - p_s) \cdot E(v \mid v \geq (r - \rho)i_s)$

We know that $(1 - p_s)E(v \mid v \geq (r - \rho)i_s) = \int_{(r-\rho)i_s}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} exp \frac{-(lnt-\mu)^2}{2\sigma^2} dt$

Denote $v(i_s) = (r - \rho)i_s$.

Assume $\phi(\frac{\ln v(i_s)-\mu}{\sigma}) \approx 0, \phi(ln(v(i_s))) \approx 0$. Take the FOC with respect to i:

$$-i_s + rp_s + \frac{\partial p_s}{\partial i_s} ri_s + (1 - p_s)\rho - \frac{\partial p_s}{\partial i_s} \rho i_s - (r - \rho)\phi(ln(v(i_s))) = 0$$

$$-i_s + rp_s + \frac{r}{\sigma}\phi(\frac{\ln v(i_s) - \mu}{\sigma}) + (1 - p_s)\rho - \frac{\rho}{\sigma}\phi(\frac{\ln v(i_s) - \mu}{\sigma}) - (r - \rho)\phi(ln(v(i_s))) = 0$$

$$rp_s + (1 - p_s)\rho \approx i_s^*$$

$$\frac{\partial i_s^*}{\partial r} = (r - \rho)\frac{\partial p_s}{\partial r} + p_s$$

$$\frac{\partial p_s}{\partial r} = \phi(\frac{\ln v(i_s) - \mu}{\sigma}) * \frac{1}{(r-\rho)\sigma}$$

$$\phi(\frac{\ln v(i_s^*) - \mu}{\sigma}) \approx 0$$

$$\implies \frac{\partial i_s^*}{\partial r} \approx p_s > 0$$

Likewise,

$$\frac{\partial i_s^*}{\partial \rho} = (r-\rho)\frac{\partial p_s}{\partial \rho} + (1-p_s)$$

$$\implies \frac{\partial i_s^*}{\partial \rho} \approx 1 - p_s > 0$$

6.2 Proposition 2

By solving for the value that optimizes Equation 3, we arrive at $\widetilde{i_0} = \widetilde{p_0}r + \frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}(r\widetilde{i_0} - w_0)$, where we denote $\widetilde{p_0} = \Phi(\frac{\ln(w_0 - \rho\widetilde{i_0}) - \mu}{\sigma}) \times 1(w_0 \geq \rho\widetilde{i_0})$. Since $\frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}} \leq 0$, $\widetilde{i_0} \leq \widetilde{p_0}r = \Phi(\frac{\ln(w_0 - \rho\widetilde{i_0}) - \mu}{\sigma})r$. Meanwhile, the firm is earning a non-negative profit, resulting in $w_0 < ri_0^*$. Since Φ is a strictly increasing function, we have $i_0^* < r\Phi(\frac{\ln(w_0 - \rho i_0^*) - \mu}{\sigma}) < r\Phi(\frac{\ln(r-\rho)i_0^*) - \mu}{\sigma})$. From Section 2.2, we know the socially efficient investment level is $i_s^* = rp_s + \rho(1-p_s)$, which means that $i_s^* > rp_s = r\Phi(\frac{\ln(r-\rho)i_s^*) - \mu}{\sigma})$. Consider the fixed point of the function $f(x) = r\Phi(\frac{\ln(r-\rho)x) - \mu}{\sigma})$. The previous inequalities imply that $i_0^* < x < i_s^*$, which proves our case.

Now, we turn to prove $p_0^* < p_s$. If a non-compete agreement is not signed, the worker will not quit if and only if $v \leq w_0 - \rho i_0^*$. For the firm to earn profits, the wage must be less than output: $w_0 < ri_0$. As a result, trade will occur when $v \leq (r-\rho)i_0^*$. For the planner, it is efficient to trade if $v \leq (r-\rho)i_s^*$. Since we have proven that $i_0^* < i_s^*$, it now follows that $p_0^* < p_s^*$.

6.3 Proposition 3

We will prove that $w_1 \geq w_0$, which will imply that $i_1^* \geq i_0^*$ and $p_1 \geq p_0$. First, as a corollary, we will prove that all compensation will be in the form of the wage and none will be in the form of the bonus. I.e. $B_1 = B_0 = 0$.

When a non-compete is not signed, we solve for equilibrium wage and investment first. From Equation 3, we can arrive at $\widetilde{i_0} = \widetilde{p_0}r + \frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}(r\widetilde{i_0} - w_0)$. Now since $\frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}} = -\rho \cdot \frac{1}{(w_0 - \rho\widetilde{i_0})\sigma} \cdot \phi(\frac{\ln(w_0-\rho\widetilde{i_0})-\mu}{\sigma}) < 0$, we know $\widetilde{i_0} < \widetilde{p_0}r$. Now onto the contracting stage, given that the worker's expected payoff binds at μ_0, we find the wage that optimizes firm profit:

$$E(\pi_0^W) = B_0 + \widetilde{p_0}w_0 + (1-\widetilde{p_0})E[v|v \geq w_0 - \rho\widetilde{i_0}] + (1-\widetilde{p_0})\rho\widetilde{i_0} = \mu_0$$

$$E(\pi_0^F) = -c(\widetilde{i_0}) - B_0 + \widetilde{p_0}(r\widetilde{i_0} - w_0)$$

$$\implies E(\pi_0^F) = -c(\widetilde{i_0}) + \widetilde{p_0}r\widetilde{i_0} - \mu_0 + \int_{w_0-\rho\widetilde{i_0}}^{\infty} \phi(ln(t))\,dt + (1-\widetilde{p_0})\rho\widetilde{i_0}$$

Now we take derivative $\frac{\partial E(\pi_0^F)}{\partial w_0}$. Note that $\widetilde{i_0}$ is a function of w_0 and $\widetilde{p_0}$ is a function of $\widetilde{i_0}$ and w_0.

$$\frac{dE(\pi_0^F)}{dw_0} = -\widetilde{i_0} \cdot \frac{d\widetilde{i_0}}{dw_0} + \frac{d\widetilde{p_0}}{dw_0} \cdot r\widetilde{i_0} + \widetilde{p_0}r\frac{d\widetilde{i_0}}{dw_0} - \phi(ln(w_0 - \rho\widetilde{i_0})) + (1-\widetilde{p_0})\rho\frac{d\widetilde{i_0}}{dw_0} - \frac{d\widetilde{p_0}}{dw_0}\rho\widetilde{i_0}$$

$$\text{where } \frac{d\widetilde{p_0}}{dw_0} = \frac{\partial\widetilde{p_0}}{\partial w_0} + \frac{\partial\widetilde{p_0}}{\partial\widetilde{i_0}} \cdot \frac{d\widetilde{i_0}}{dw_0}$$

Assuming $\phi(ln(w_0 - \rho\widetilde{i_0})) \approx 0$,

$$\frac{dE(\pi_0^F)}{dw_0} = \overbrace{(-\widetilde{i_0} + \widetilde{p_0}r + (1-\widetilde{p_0})\rho)}^{>0 \text{ as } \widetilde{i_0}<\widetilde{p_0}r} \cdot \frac{d\widetilde{i_0}}{dw_0} + \frac{d\widetilde{p_0}}{dw_0} \cdot \overbrace{(r\widetilde{i_0} - \rho\widetilde{i_0})}^{>0 \text{ as } r>\rho}$$

To determine the sign of $\frac{dE(\pi_0^F)}{dw_0}$, we need to know the signs of $\frac{d\widetilde{i_0}}{dw_0}$ and $\frac{d\widetilde{p_0}}{dw_0}$. To determine how investment responds to the wage, take the total derivative of the following: $\widetilde{i_0} = \widetilde{p_0} r + \frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}(r\widetilde{i_0} - w_0)$

$$\begin{aligned}
\frac{d\widetilde{i_0}}{dw_0} &= \frac{d\widetilde{p_0}}{dw_0} r + \overbrace{\frac{\partial^2 \widetilde{p_0}}{\partial \widetilde{i_0} \partial w_0}}^{\approx 0}(r\widetilde{i_0} - w_0) + \overbrace{\frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}}^{<0}(r\frac{d\widetilde{i_0}}{dw_0} - 1) \\
\frac{d\widetilde{i_0}}{dw_0} &= r(\frac{\partial \widetilde{p_0}}{\partial w_0} + \frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}} \cdot \frac{d\widetilde{i_0}}{dw_0}) - \frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}
\end{aligned}$$

$$\implies \overbrace{(1 - r\overbrace{\frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}}^{<0})}^{>0} \cdot \frac{d\widetilde{i_0}}{dw_0} = r\overbrace{\frac{\partial \widetilde{p_0}}{\partial w_0}}^{>0} - \overbrace{\frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}}}^{<0}$$

This implies that $\frac{d\widetilde{i_0}}{dw_0} > 0$. Assume $\frac{\partial \widetilde{p_0}}{\partial w_0} >> \frac{\partial \widetilde{p_0}}{\partial \widetilde{i_0}} \cdot \frac{d\widetilde{i_0}}{dw_0}$, so that $\frac{d\widetilde{p_0}}{dw_0} > 0$. Thus $\frac{dE(\pi_0^F)}{dw_0} > 0$ for all w_0 that satisfies the utility constraint. Given this, the profit is maximized at the higher bound for w_0, which happens when we have $B_0 = 0$.[39]

The equilibrium w_0^* satisfies the following equation:

$$p_0^* w_0^* + (1 - p_0^*) E[v | v \geq w_0^* - \rho i_0^*] + (1 - p_0^*) \rho i_0^* = \mu_0$$

With this, we can also solve for the investment i_0^*. Now that we have the first period wage and optimal investment solved implicitly, we can see how i_0^* changes with ρ. Taking the total derivative of the function above with respect to ρ, we have

$$\frac{dp_0^*}{d\rho} w_0^* + p_0^* \cdot \frac{dw_0^*}{d\rho} - \phi(ln(w_0^* - \rho i_0^*)) i_0^* - \frac{dp_0^*}{d\rho} \rho i_0^* + (1 - p_0^*) i_0^* + (1 - p_0^*) \rho \frac{di_0^*}{d\rho} = 0$$

$$\implies (1 - p_0^*)[i_0^* + \frac{\partial i_0^*}{\partial \rho} \rho] + p_0^* \frac{\partial w_0^*}{\partial \rho} \approx 0 \tag{7}$$

Now to learn the sign for $\frac{di_0^*}{d\rho}$ and $\frac{dw_0^*}{d\rho}$, we can turn to the optimal investment function $i_0^* = p_0^* r + \frac{\partial p_0^*}{\partial i_0^*}(r i_0^* - w_0^*)$

[39] This occurs because $\frac{\partial E(\pi_0^F)}{\partial w_0} > 0$.

Taking the total derivative of the function with respect to the variable ρ, we have

$$\frac{di_0^*}{d\rho} = r\cdot(\frac{\partial p_0^*}{\partial w_0^*} + \frac{\partial p_0^*}{\partial i_0^*}\cdot\frac{di_0^*}{dw_0^*}) + \overbrace{\frac{\partial^2 p_0^*}{\partial i_0^* \partial \rho}}^{\approx 0}(i_0^* - w_0^*) + \frac{\partial p_0^*}{\partial i_0^*}(r\frac{di_0^*}{d\rho} - \frac{dw_0^*}{d\rho})$$

$$\implies \overbrace{(1 - 2\overbrace{\frac{\partial p_0^*}{\partial i_0^*}}^{<0})}^{>0}\frac{di_0^*}{d\rho} = \overbrace{(r\cdot\overbrace{\frac{\partial p_0^*}{\partial w_0^*}}^{>0} - \overbrace{\frac{\partial p_0^*}{\partial i_0^*}}^{<0})}^{>0}\cdot\frac{dw_0^*}{d\rho}$$

From the optimal investment equation, we can see that $\frac{di_0^*}{d\rho}$ and $\frac{dw_0^*}{d\rho}$ have the same sign. Thus we can denote $\frac{di_0^*}{d\rho} = k\frac{dw_0^*}{d\rho}$ with $k > 0$.

Plugging into Equation 7, we have

$$\Big(\overbrace{(1-p_0^*)\rho + p_0^* k}^{>0}\Big)\frac{di_0^*}{d\rho} \approx -(1-p_0^*)i_0^* < 0$$

We have successfully proven that $\frac{di_0^*}{d\rho} < 0$, which implies that $i_0^* < i_1^*, \forall\rho > 0$.

Likewise, when $\rho = 0$, we have $w_0^* = w_1^*$. And since $\frac{di_0^*}{d\rho} = \overbrace{k}^{>0}\overbrace{\frac{dw_0^*}{d\rho}}^{<0} < 0$, we also have $w_0^* < w_1^*$.

Lastly, with $\delta = 1$, trading occurs when $v \leq w_1^*$, and with $\delta = 0$, trading occurs when $v \leq w_0^* - \rho i_0^*$. From $w_1^* > w_0^*$, we have $w_0^* - \rho i_0^* < w_1^*$. Thus we have $p_0^* < p_1^*$, meaning there is a higher probability of separation when a non-compete agreement is not signed.

6.4 Proposition 4

When $\rho > r$, we have already shown that all contracts without non-compete agreements generate zero or negative profits, so will not be used. We just need to show that there exists a contract with a non-compete agreement that generates positive profits. Such an illustration will prove that a non-compete agreement will be used.

From Equation 3, we can arrive at $\widetilde{i_1} = \widetilde{p}_1 r$, where we denote $\widetilde{p}_1 = \Phi(\frac{\ln w_1 - \mu}{\sigma})$. Now onto the contracting stage, given that the worker's expected payoff binds at μ_0, we find the wage that optimizes firm profit:

$$E(\pi_1^W) = B_1 + \widetilde{p_1} w_1 + (1-\widetilde{p_1})E[v|v \geq w_1] = \mu_0$$

$$E(\pi_1^F) = -c(\widetilde{i_1}) - B_1 + \widetilde{p_1}(r\widetilde{i_1} - w_1)$$

$$\implies w_1^* = \text{argmax } E(\pi_1^F) = -c(\widetilde{i_1}) + \widetilde{p_1} r\widetilde{i_1} - \mu_0 + (1-\widetilde{p_1})E[v|v \geq w_1] \text{ s.t. } B_1 \geq 0, E(\pi_1^F) \geq 0$$

Solving for the optimization problem using Karush–Kuhn–Tucker conditions, we know the profit is maximized at the higher bound for w_1, which happens when we have $B_1 = 0$ binding. The equilibrium w_1^* satisfies the following equation.[40]

$$p_1^* w_1^* + (1-p_1^*)E[v|v \geq w_1^*] = \mu_0$$

Plugging this value into the equation for $\tilde{i_1}$, we solve for $i_1^* = p_1^* r$. As long as $E(\pi_1^F(w_1^*)) \geq 0$, there will be a contract that includes a non-compete agreement. Thus when $r < \rho$, a non-compete agreement will be used.

When $r > \rho$, it is ambiguous whether the firm chooses to include a non-compete agreement in the contract. Observe that $\frac{\partial E(\pi_0^F)}{\partial \rho} = \frac{\partial p_0^*}{\partial \rho}(ri_0^* - w_0^*(\rho)) - p_0^* \frac{\partial w_0^*}{\partial \rho}$. The first term is negative while the second term is positive, so the sign of the overall expression is ambiguous.

A Monopsonistic Model

We make several changes to develop a monopsonistic model that may better reflect the dynamics with non-compete agreements for low wage workers. First and foremost, we assume that there is a measure 1 of workers on the unit interval $[0,1]$ with different initial outside options, instead of one worker with a fixed outside option. Workers' first period outside options, denoted as μ_0^j, with

[40] It is assumed there is a single solution to the equation below.

j indicating different workers, are distributed log normally with mean η and variance σ^2. The firm can only choose one wage, which will determine the level of employment, in order to maximize its expected profit. We additionally assume that investment i is exogenous to simplify the model.

First, we solve the social planner's problem. The social planner in this case determines the efficient level of employment. In the last period, it is efficient to trade if and only if $v \leq (r-\rho)i$. Denote the probability that trading is efficient as p_s. In the first stage, the planner matches workers to the monopsonistic firm only if the expected surplus from the match is greater than the worker's ex-ante outside option. We denote the efficient employment level as $q_s = P(E(S) \geq \mu_0^j)$, where

$$E(S) = -c(i) + p_s ri + (1-p_s)\rho i + (1-p_s) \cdot E(v \mid v \geq (r-\rho)i_s)$$

Now we solve the firm's decisions. In the last period, the worker will not quit so long as $w_\delta \geq v + \rho i(1-\delta)$. We denote the probability of trade as p_δ, which does not depend on the identity of the worker. Now in the first period, the firm chooses the wage to maximize its profit. Given a wage w_δ, we denote the proportion of workers agreeing to the contract as $q_\delta = P(E(\pi_\delta^W) \geq \mu_0^j)$. Thus, the firm chooses the wage that maximizes the following equation:

$$E(\pi_\delta^F) = q_\delta[-c(i) + p_\delta(ri - w_\delta)]$$

Proposition A1: Employment without a non-compete agreement is less than the socially efficient level ($q_0 \leq q_s$).

Proof. Given that $q_0 = P(E(\pi_0^W) \geq \mu_0^j)$ and $q_s = P(E(S) \geq \mu_0^j)$, we only need to show that $E(\pi_0^W) \leq E(S)$ in order to prove $q_0 \leq q_s$.

$$E(\pi_0^W) = p_0^* \cdot w_0^* + (1-p_0^*)\rho i + (1-p_0) \cdot E(v \mid v \geq (w_0^* - \rho i)$$

In any contract, we know $w_0^* \leq ri$, since the firm must earn non-negative profits ex-post. Thus $w_0 - \rho i \leq (r-\rho)i$, which means $p_0^* \leq p_s^*$. In addition, the firm chooses wages so that it earns non-negative profits ex-post: $-c(i) + p_0(ri - w_0) \geq 0$.

Now we can compare $E(S)$ with $E(\pi_0^W)$.

$$
\begin{aligned}
E(S)-E(\pi_0^W) &= -c(i)+p_s ri - p_0 w_0 - (p_s-p_0)\rho i - \int_{w_0^*-\rho i}^{(r-\rho)i} \phi(ln(t))\,dt \\
&= \overbrace{-c(i)+p_0(ri-w_0)}^{\geq 0} + (p_s-p_0)(r-\rho)i - (p_s-p_0)E(v \mid v \in [w_0^*-\rho i,(r-\rho)i]) \\
&\geq \overbrace{(p_s-p_0)}^{\geq 0}[(r-\rho)i - \overbrace{E(v \mid v \in [w_0^*-\rho i,(r-\rho)i])}^{\leq (r-\rho)i}] \\
&\geq 0
\end{aligned}
$$

This is the proof of the well-known result that employment under a monopsony is less than socially efficient.

Proposition A2: The effect of non-compete agreements on wages is theoretically ambiguous.

Proof. When $\delta = 0$, take FOC we have

$$
\frac{dq_0^*}{dw_0^*}\cdot[-c(i)+p_0^*(ri-w_0^*)] + q_0^*\cdot[\frac{dp_0^*}{dw_0^*}(ri-w_0^*)-p_0^*] = 0 \tag{8}
$$

Now to compare the wage with and without a non-compete, like in Proposition 3, we only need to check $\frac{dw_0^*}{d\rho}$. From the equation above, we can take total derivative in terms of q and assuming that $\frac{d^2 q_0^*}{dw_0^* d\rho} \approx 0$ we get

$$
\frac{dq_0^*}{dw_0^*}\cdot[\frac{dp_0^*}{d\rho}\cdot(ri-w_0^*) - p_0^*\cdot\frac{dw_0^*}{d\rho}] + \frac{dq_0^*}{d\rho}\cdot[\frac{dp_0^*}{dw_0^*}(ri-w_0^*)-p_0^*] + q_0^*\cdot[-\frac{dp_0^*}{dw_0^*}\cdot\frac{dw_0^*}{d\rho} - \frac{dp_0^*}{d\rho}] = 0
$$

$$
\text{where } \frac{dp_0^*}{d\rho} = \frac{\partial p_0^*}{\partial \rho} + \frac{dp_0^*}{dw_0^*}\cdot\frac{dw_0^*}{d\rho} \text{ and } \frac{dq_0^*}{d\rho} = \frac{dq_0^*}{dw_0^*}\cdot\frac{dw_0^*}{d\rho} + \frac{\partial q_0^*}{\partial \rho}
$$

$$
\Longrightarrow 2[\frac{dq_0^*}{dw_0^*}\cdot(\frac{dp_0^*}{dw_0^*}(ri-w_0^*)-p_0^*) - q_0^*\cdot\frac{dp_0^*}{dw_0^*})]\frac{dw_0^*}{d\rho} = \frac{\partial p_0^*}{\partial \rho}\cdot[q_0^* - \frac{dq_0^*}{dw_0^*}\cdot(ri-w_0^*)] - \frac{\partial q_0^*}{\partial \rho}[\frac{dp_0^*}{dw_0^*}(ri-w_0^*)-p_0^*] \tag{9}
$$

From equation 1 above, since we have

$$\overbrace{\frac{dq_0^*}{dw_0^*} \cdot [-c(i) + p_0^*(ri - w_0^*)]}^{\geq 0} + \overbrace{q_0^*}^{\geq 0} \cdot [\frac{dp_0^*}{dw_0^*}(ri - w_0^*) - p_0^*] = 0 \tag{10}$$

$$\implies \frac{dp_0^*}{dw_0^*}(ri - w_0^*) - p_0^* \leq 0$$

Thus from equation 2 we have

$$2[\overbrace{\frac{dq_0^*}{dw_0^*} \cdot (\frac{dp_0^*}{dw_0^*}(ri - w_0^*) - p_0^*) - q_0^* \cdot \frac{dp_0^*}{dw_0^*})]}^{\leq 0} \frac{dw_0^*}{d\rho} = \overbrace{\frac{\partial p_0^*}{\partial \rho}}^{<0} \cdot [q_0^* - \frac{dq_0^*}{dw_0^*} \cdot (ri - w_0^*)] - \frac{\partial q_0^*}{\partial \rho} \overbrace{[\frac{dp_0^*}{dw_0^*}(ri - w_0^*) - p_0^*]}^{\leq 0} \tag{11}$$

It is unclear whether w_0^* increases with ρ or not without knowing more about the distributions of q_0 and p_0. If $\frac{dw_0^*}{d\rho} > 0$, then we know that the wage is higher without a non-compete agreement.

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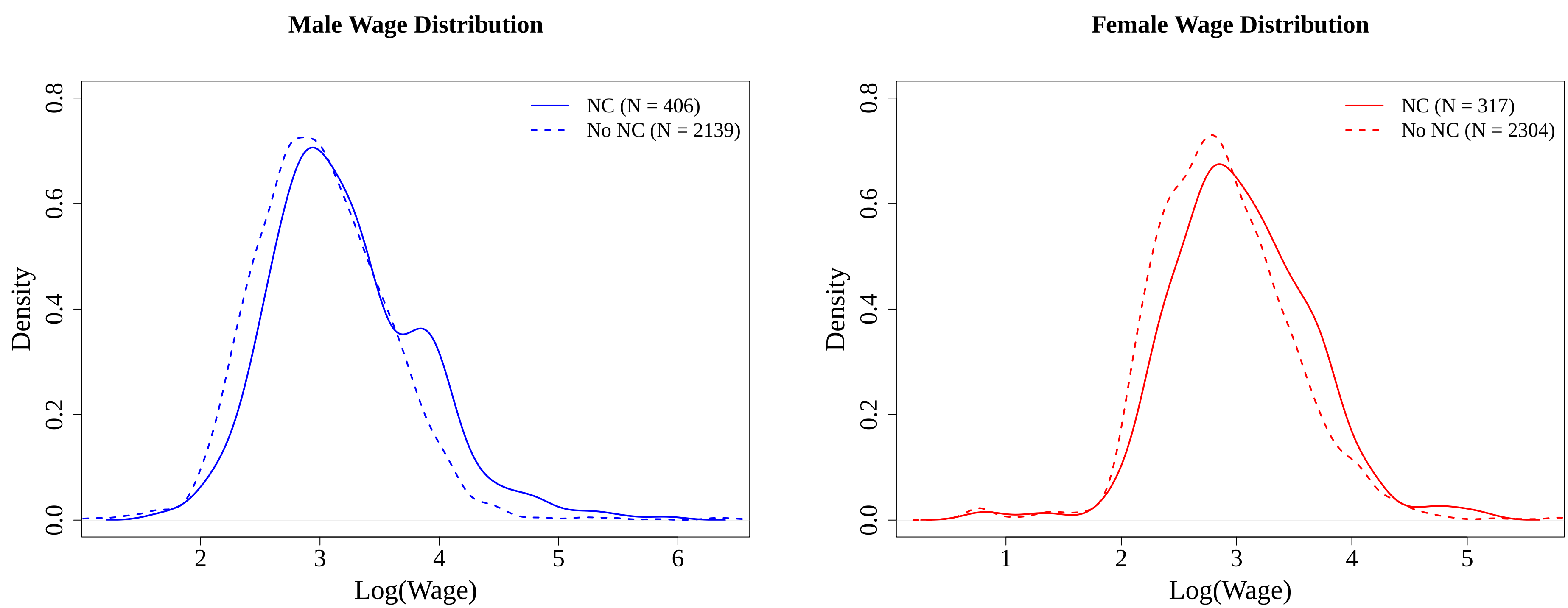
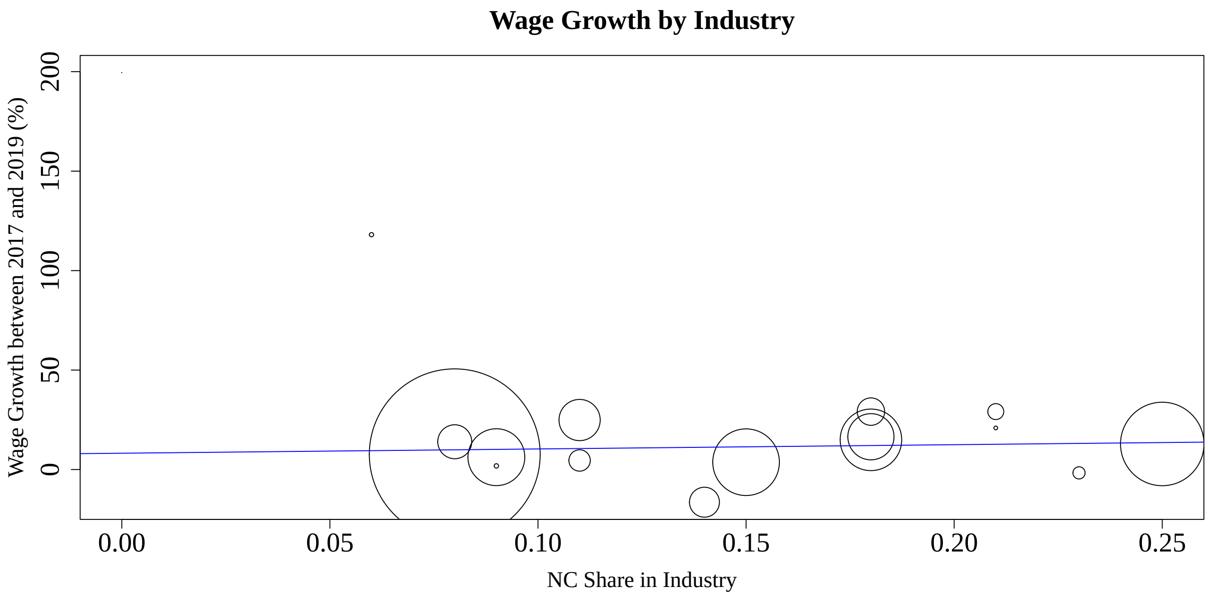
Figure 4



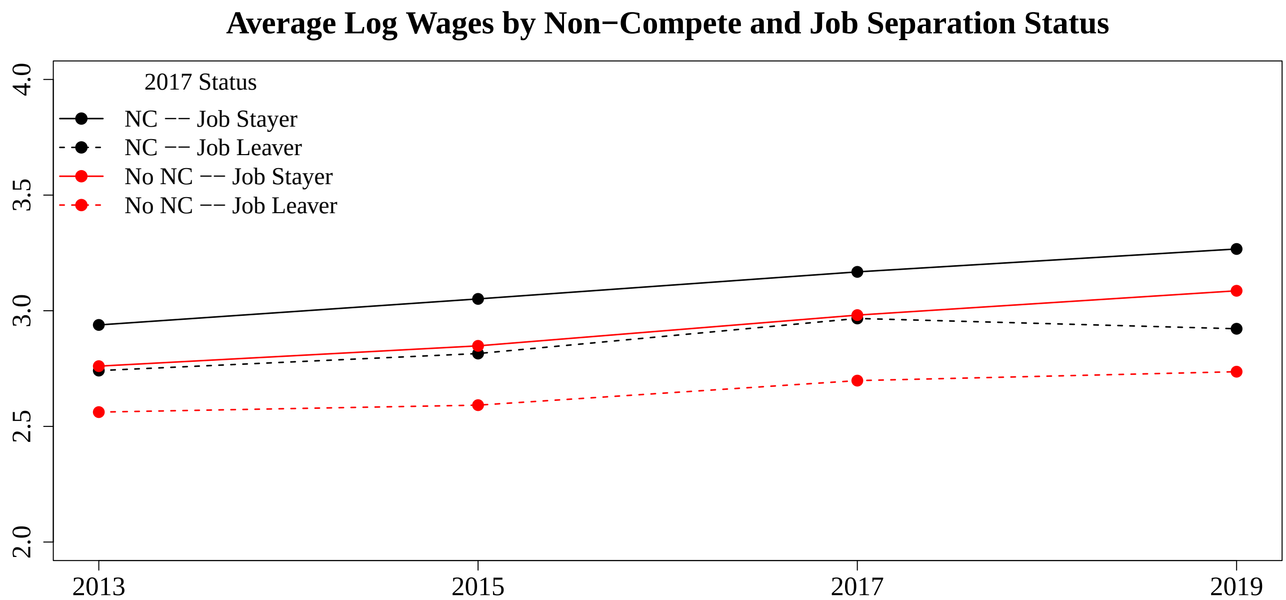
Note: The sample consists of respondents in the NLSY97 who report non−compete status in their main job in 2017. Nominal wages are measured in dollars earned per hour.

Figure 5



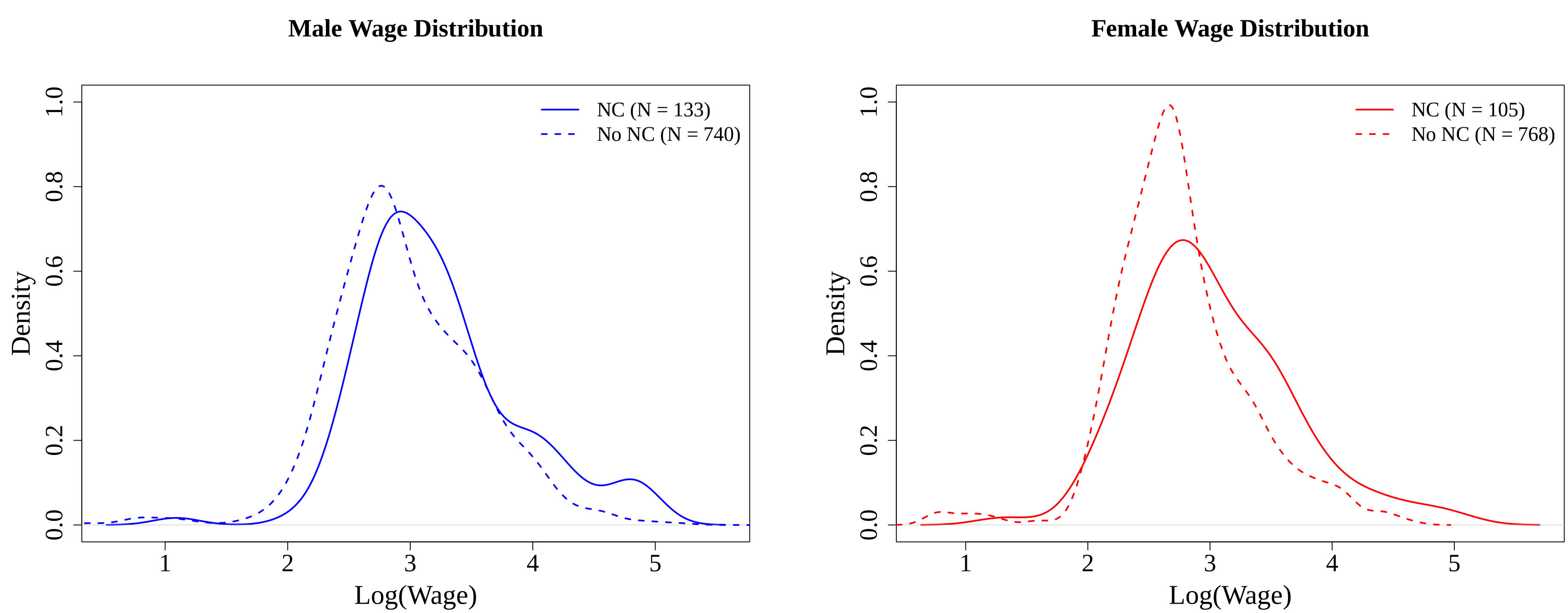
Note: The figure presents the percentage change in mean industry wages between 2017 and 2019 versus non−compete usage by industry in 2017. The size of the circles are proportional to industry size and the line of best fit is weighted by industry size. The slope is 21.43 (SE = 55) and the intercept is 8.2. The wage is measured in terms of dollars earned per hour.

Figure 6



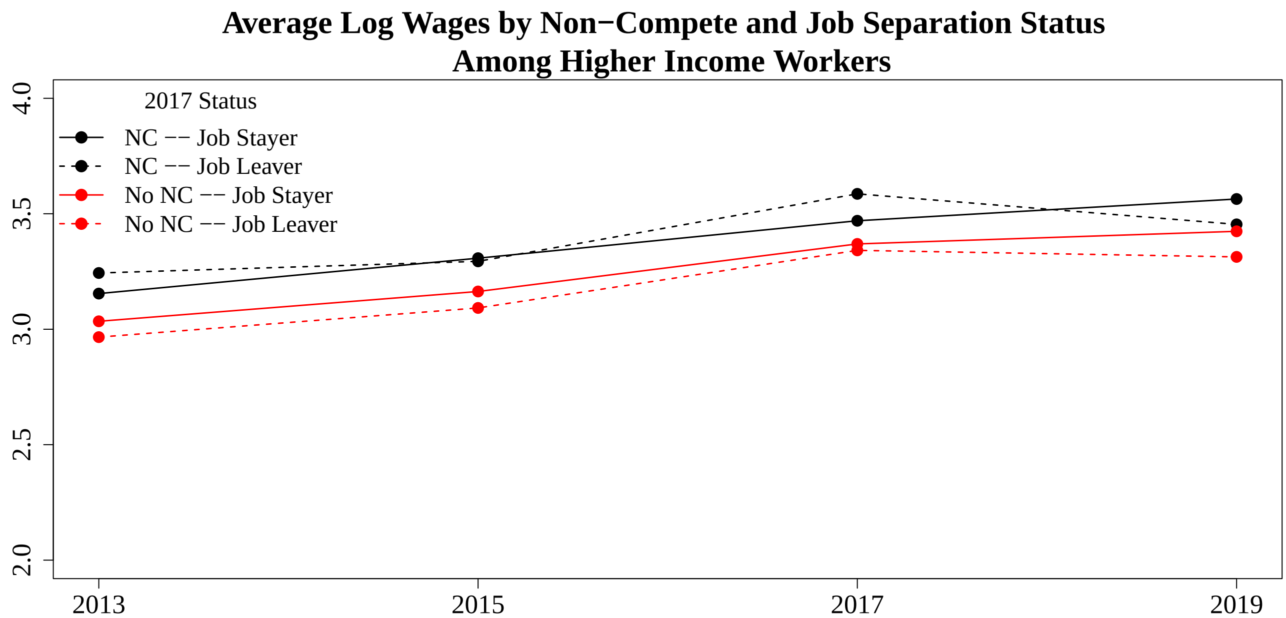
Note: The sample tracks respondents with valid non−compete status in 2017, the first year the non−compete question is available. For job stayers (leavers), the primary employer in 2017 (does not) appears in the 2019 employer roster. The wage is measured for the main employer and in terms of dollars earned per hour.

Figure A1



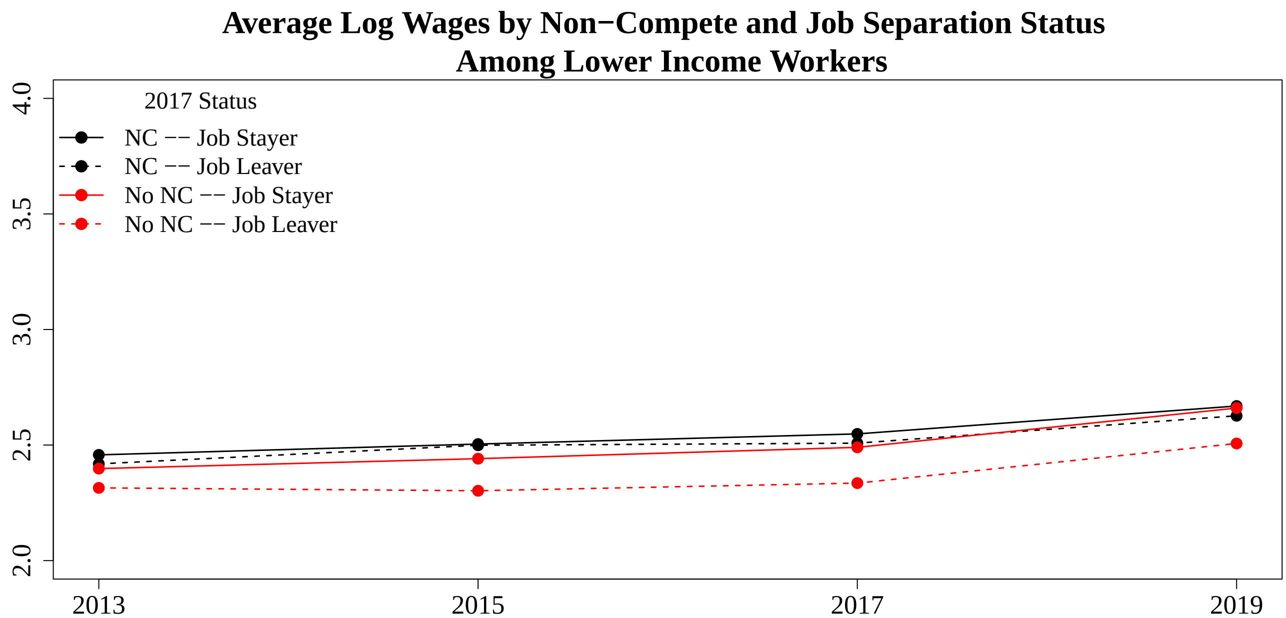
Note: The sample consists of respondents in the NLSY97 who report non−compete status in their main job in 2019. These respondents obtained new jobs between the 2017 and 2019 survey periods. Nominal wages are measured in dollars earned per hour.

Figure A2



Note: The sample tracks respondents with valid non−compete status in 2017, the first year the non−compete question is available. For job stayers (leavers), the primary employer in 2017 (does not) appears in the 2019 employer roster. The wage is measured for the main employer and in terms of dollars earned per hour. Higher−income workers earn above median wages in 2017.

Figure A3



Note: The sample tracks respondents with valid non−compete status in 2017, the first year the non−compete question is available. For job stayers (leavers), the primary employer in 2017 (does not) appears in the 2019 employer roster. The wage is measured for the main employer and in terms of dollars earned per hour. Lower−income workers earn below median wages in 2017.

Table 1: Usage of Non-Compete Agreements by Industry

	NC Status			
Industry	Yes	No	Total	Share Yes
PROFESSIONAL AND RELATED SERVICES	159	463	622	0.26
INFORMATION AND COMMUNICATION	21	70	91	0.23
MINING	6	22	28	0.21
WHOLESALE TRADE	25	94	119	0.21
MANUFACTURING	82	377	459	0.18
FINANCE, INSURANCE, AND REAL ESTATE	63	282	345	0.18
ACS SPECIAL CODES	36	169	205	0.18
RETAIL TRADE	74	424	498	0.15
TRANSPORTATION AND WAREHOUSING	31	193	224	0.14
CONSTRUCTION	34	274	308	0.11
OTHER SERVICES	18	142	160	0.11
UTILITIES	3	30	33	0.09
ENTERTAINMENT, ACCOMODATIONS, AND FOOD SERVICES	37	388	425	0.09
EDUCATIONAL, HEALTH, AND SOCIAL SERVICES	101	1176	1277	0.08
PUBLIC ADMINISTRATION	21	233	254	0.08
AGRICULTURE, FORESTRY AND FISHERIES	2	30	32	0.06
ACTIVE DUTY MILITARY	0	1	1	0.00
TOTAL	713	4368	5081	0.14

Note:
The sample consists of NLSY97 respondents who report non-compete status, confidence in response, and industry status in 2017. Rows are organized by non-compete share in the industry.

Table 2: Respondent Characteristics by Non-Compete Status

	NC	No NC	Difference	P Value	N: NC	N: No NC
Tenure and Job Separation						
Tenure (Yrs)	5.16	4.86	0.30	0.10	690	4202
1(Job Separation btwn 2017 and 2019)	0.13	0.18	-0.05	0.00	695	4276
Wages and Wage Growth						
Starting Wage	22.88	18.55	4.34	0.00	695	4276
Wage in 2017	28.02	22.33	5.69	0.00	695	4276
Wage in 2019	31.19	25.21	5.98	0.00	625	3765
$Log(Wage_{2017}) - Log(Wage_{2015})$	0.13	0.14	-0.01	0.51	620	3793
$Log(Wage_{2019}) - Log(Wage_{2017})$	0.10	0.11	-0.01	0.63	625	3765
Demographics						
Age	34.99	34.94	0.05	0.37	695	4276
1(Male)	0.57	0.48	0.09	0.00	695	4276
1(High School Degree or Higher)	0.87	0.84	0.03	0.02	688	4238
1(Bachelors Degree or Higher)	0.47	0.37	0.10	0.00	688	4238
Training						
1(Received Some Training)	0.29	0.27	0.03	0.17	695	4276

Table 2: Respondent Characteristics by Non-Compete Status *(continued)*

	NC	No NC	Difference	P Value	N: NC	N: No NC
1(Received Training Run by Employer)	0.13	0.11	0.02	0.11	695	4276
1(Received On-Site Training by Non-Employer)	0.06	0.05	0.01	0.25	695	4276
1(Employer Paid for Training)	0.22	0.20	0.03	0.10	695	4276
1(Employer Paid for Mandatory Training)	0.18	0.14	0.04	0.01	695	4276
1(Employer Paid for Voluntary Training)	0.11	0.10	0.00	0.86	695	4276

Note:

The sample includes respondents with valid non-compete status for the main employer in 2017. All wage variables are measured in terms of dollars earned per hour. Respondents earning zero wages are dropped. The training variables capture whether the respondent has ever previously received a given type of training with their main employer as of 2017. Raw means and p-values from a two-sided t-test are reported. Sample sizes vary due to missing values of the outcome variable.

Table 3: Training by Non-Compete Status

	Employer Paid for Training				Training Run by Employer				Received Some Training			
	NC	No NC	Difference	P-Value	NC	No NC	Difference	P-Value	NC	No NC	Difference	P-Value
High NC Share Industries	0.24	0.18	0.06	0.01	0.15	0.11	0.04	0.02	0.30	0.24	0.06	0.02
Low NC Share Industries	0.20	0.21	-0.01	0.73	0.11	0.12	-0.01	0.66	0.28	0.28	-0.01	0.80
High NC Share Occupations	0.27	0.25	0.02	0.39	0.17	0.14	0.03	0.15	0.33	0.31	0.02	0.49
Low NC Share Occupations	0.17	0.17	0.00	0.98	0.09	0.10	0.00	0.79	0.25	0.24	0.01	0.82
High Wage Earners	0.31	0.28	0.02	0.37	0.18	0.16	0.02	0.29	0.36	0.35	0.01	0.69
Low Wage Earners	0.10	0.12	-0.01	0.44	0.06	0.07	-0.01	0.70	0.19	0.19	0.00	0.98

Note:

The sample includes respondents with valid non-compete status in 2017. The outcomes refer to whether the respondent ever received a certain type of training while working for the main employer as of 2017. High NC Share Industries (Occupations) are those with above average NC usage in the industry (occupation). High wage earners are those earning above median wages as of 2017. Raw means and p-values from a two sided t-test are reported.

Table 4: Wage Growth between 2017 and 2019 by Non-Compete Status

	NC	No NC	Difference	P Value
Full Sample	0.10	0.11	-0.01	0.63
Higher Income	0.08	0.05	0.03	0.11
Lower Income	0.13	0.16	-0.03	0.32
Bachelors Degree or Higher	0.10	0.10	0.00	0.93
No Bachelors Degree	0.09	0.11	-0.02	0.48
Male	0.08	0.12	-0.04	0.18
Female	0.12	0.10	0.02	0.25

Note:

The sample includes respondents in the NLSY97 who report the non-compete status of their main job in 2017. It further restricts to individuals with valid wage information in their main job in 2017 and 2019. Wage growth is measured as the log of 2019 wages less the log of 2017 wages. Higher (Lower) income respondents earn above (below) median wages in 2017. Raw means and p-values from a two sided t-test reported.

Table 5: Effects of Non-Compete Agreements
Using the Never-Treated as a Control Group

	Relative Time	Log(Wages)	Wage Growth	1(Job Separation)	1(Any Training)	1(Employer Paid for Training)
	-6	-0.04 (0.046)	-0.132 (0.057)	-0.092 (0.033)	0.024 (0.043)	0.071 (0.039)
	-4	-0.003 (0.034)	-0.03 (0.063)	-0.077 (0.028)	0.061 (0.028)	0.056 (0.022)
	-2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	0	0.07 (0.033)	0.052 (0.055)	-0.089 (0.024)	0.016 (0.021)	0.024 (0.018)
	2	0.104 (0.034)	-0.048 (0.04)	-0.079 (0.033)	0.005 (0.023)	0.026 (0.019)
	4	0.127 (0.059)	-0.156 (0.067)	-0.026 (0.055)	0.016 (0.034)	0.053 (0.027)
	6	0.093 (0.095)	-0.12 (0.071)		0.008 (0.055)	0.018 (0.041)
N obs		6918	6918	5524	6918	6918
N: Treated		457	457	457	457	457
N: Never Treated		988	988	988	988	988
Dependent Variable Mean		3.005	0.1	0.031	0.135	0.104

Note:
The sample restricts to a unbalanced panel of individuals observed between 2011 and 2019, and who report non-compete status in 2017. Effects using the Callaway and Sant'anna estimator are relative to the survey year (two calendar years) prior to the adoption of non-compete agreements. Treated individuals adopt non-compete agreements in 2013, 2015, or 2017. Individuals who are "always-treated" – those that receive treatment before 2013 – are dropped. Individuals without non-compete agreements who do not fall under the "never-treated" category – those without non-compete agreements between 2011-2019 – are also excluded. Standard errors are clustered at the individual level. All columnns are derived from the NLSY97 Public Use Files. Sample sizes vary due to missing values.

Table A1: Confidence in Non-Compete Status by Industry

Industry	NC Confidence			Total	Share Very Confident
	Very Confident	Somewhat Confident	Not Confident		
ACTIVE DUTY MILITARY	1	0	0	1	1.00
AGRICULTURE, FORESTRY AND FISHERIES	31	0	1	32	0.97
CONSTRUCTION	290	14	4	308	0.94
OTHER SERVICES	150	8	2	160	0.94
TRANSPORTATION AND WAREHOUSING	205	12	7	224	0.92
EDUCATIONAL, HEALTH, AND SOCIAL SERVICES	1173	95	9	1277	0.92
ACS SPECIAL CODES	188	16	1	205	0.92
UTILITIES	30	3	0	33	0.91
INFORMATION AND COMMUNICATION	83	8	0	91	0.91
FINANCE, INSURANCE, AND REAL ESTATE	313	29	3	345	0.91
ENTERTAINMENT, ACCOMODATIONS, AND FOOD SERVICES	388	34	3	425	0.91
PUBLIC ADMINISTRATION	232	21	1	254	0.91
MANUFACTURING	412	43	4	459	0.90
MINING	25	3	0	28	0.89
WHOLESALE TRADE	106	12	1	119	0.89
RETAIL TRADE	443	50	5	498	0.89
PROFESSIONAL AND RELATED SERVICES	550	65	7	622	0.88
TOTAL	4620	413	48	5081	0.91

Note:
The sample consists of NLSY97 respondents who report non-compete, non-compete confidence, and industry status in 2017. Rows are organized by share "Very Confident" in response to the non-compete confidence question.

Table A2: Usage of Non-Compete Agreements by Industry in 2019

	NC Status			
Industry	Yes	No	Total	Share Yes
WHOLESALE TRADE	17	32	49	0.35
PROFESSIONAL AND RELATED SERVICES	49	159	208	0.24
FINANCE, INSURANCE, AND REAL ESTATE	23	84	107	0.21
UTILITIES	3	12	15	0.20
MANUFACTURING	31	160	191	0.16
TRANSPORTATION AND WAREHOUSING	14	83	97	0.14
OTHER SERVICES	8	48	56	0.14
CONSTRUCTION	14	107	121	0.12
INFORMATION AND COMMUNICATION	3	26	29	0.10
ENTERTAINMENT, ACCOMODATIONS, AND FOOD SERVICES	19	171	190	0.10
EDUCATIONAL, HEALTH, AND SOCIAL SERVICES	35	369	404	0.09
RETAIL TRADE	13	152	165	0.08
MINING	1	15	16	0.06
PUBLIC ADMINISTRATION	3	55	58	0.05
AGRICULTURE, FORESTRY AND FISHERIES	0	7	7	0.00
ACS SPECIAL CODES	0	3	3	0.00
TOTAL	233	1483	1716	0.14

Note:
The sample consists of NLSY97 respondents who report non-compete status, confidence in response, and industry status in 2019. Rows are organized by non-compete share in the industry.

Table A3: Relationship between Non-Compete Agreements and Log(Wages) in 2019

Dependent Variable:	Log(Wage)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
1(NC)	0.285***	0.277***	0.257***	0.241***	0.200***	0.161***
	(0.046)	(0.046)	(0.045)	(0.045)	(0.040)	(0.039)
Tenure (Yrs)		0.039***	0.036***	0.034***	0.028***	0.025***
		(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Schooling (Yrs)			0.028***	0.029***	0.115***	0.104***
			(0.007)	(0.008)	(0.012)	(0.011)
1(Male)				0.229***	0.270***	0.202***
				(0.031)	(0.028)	(0.029)
Potential Experience					0.020**	0.018*
					(0.010)	(0.009)
Fixed-effects						
Industry						Yes
Fit statistics						
Observations	1,690	1,670	1,646	1,646	1,640	1,612
Dependent variable mean	2.89	2.90	2.90	2.90	2.90	2.90
R^2	0.023	0.032	0.092	0.123	0.256	0.365

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: All specifications include respondents with valid wage and non-compete status in 2019. The sample further restricts to individuals' main job in 2019. The wage variable is measured in dollars earned per hour. Potential experience = Age - Highest Educational Grade - 6. There are 17 industries, as reflected in Table 1.

Table A4: Relationship between Non-Compete Agreements and Wage Growth

Dependent Variable:	Wage Growth between 2017 and 2019					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
1(NC)	0.0006	6.85×10^{-5}	-0.006	-0.009	-0.008	-0.009
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Tenure (Yrs)		-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Schooling (Yrs)			0.003**	0.003**	0.004	0.007
			(0.001)	(0.001)	(0.005)	(0.005)
1(Male)				0.024*	0.023*	0.018
				(0.013)	(0.013)	(0.014)
Potential Experience					0.0006	0.002
					(0.004)	(0.004)
Fixed-effects						
Industry						Yes
Fit statistics						
Observations	4,971	4,892	4,850	4,850	4,843	4,770
Dependent variable mean	0.156	0.156	0.155	0.155	0.155	0.153
R^2	2.05×10^{-7}	0.002	0.003	0.003	0.003	0.013

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: All specifications include respondents with valid wage growth inforation and non-compete status in 2017. The sample further restricts to individuals' main job in 2017. Wage growth is measured as the percentage change in nominal wages between 2017 and 2019. The wage growth variable only considers the change in wages within an individual's main job. Potential experience = Age - Highest Educational Grade - 6. There are 17 industries, as reflected in Table 1.

Table A5: Relationship between Non-Compete Agreements and Log(Wages) in 2017

Dependent Variable:	Log(Wage)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
1(NC)	0.211***	0.202***	0.188***	0.174***	0.138***	0.112***
	(0.025)	(0.025)	(0.024)	(0.023)	(0.021)	(0.021)
Tenure (Yrs)		0.028***	0.026***	0.026***	0.022***	0.022***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Schooling (Yrs)			0.045***	0.047***	0.108***	0.103***
			(0.009)	(0.009)	(0.006)	(0.007)
1(Male)				0.150***	0.197***	0.143***
				(0.019)	(0.015)	(0.017)
Potential Experience					0.014**	0.012**
					(0.005)	(0.005)
Fixed-effects						
Industry						Yes
Fit statistics						
Observations	4,971	4,892	4,850	4,850	4,843	4,770
Dependent variable mean	2.96	2.96	2.97	2.97	2.97	2.97
R^2	0.014	0.054	0.151	0.165	0.271	0.331

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: All specifications include respondents with valid wage and non-compete status in 2017. The sample further restricts to individuals' main job in 2017. The wage variable is measured in dollars earned per hour. Potential experience = Age - Highest Educational Grade - 6. There are 17 industries, as reflected in Table 1.

Table A6: Relationship between Non-Compete Agreements and Employer-Paid Training in 2017

Dependent Variable:	1 (Prior Emp-Paid Training)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
1(NC)	0.025	0.016	0.013	0.012	0.006	0.017
	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Tenure (Yrs)		0.030***	0.030***	0.030***	0.030***	0.028***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Schooling (Yrs)			0.007***	0.007***	0.015***	0.012***
			(0.002)	(0.002)	(0.004)	(0.004)
1(Male)				0.008	0.017	0.021*
				(0.011)	(0.011)	(0.012)
Potential Experience					-0.001	9.27×10^{-5}
					(0.004)	(0.004)
Fixed-effects						
Industry						Yes
Fit statistics						
Observations	4,971	4,892	4,850	4,850	4,843	4,770
Dependent variable mean	0.196	0.196	0.196	0.196	0.196	0.196
R^2	0.0005	0.120	0.126	0.127	0.136	0.170

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: All specifications include respondents with valid wage and non-compete status in 2017. The outcome variable indicates whether a respondent ever previously received employer-paid training with their main employer as of 2017. Potential experience = Age - Highest Educational Grade - 6. There are 17 industries, as reflected in Table 1.

Table A7: Relationship between Non-Compete Agreements and Job Separation between 2017 and 2019

Dependent Variable:	1(Job Separation)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
1(NC)	-0.051***	-0.046***	-0.041***	-0.038***	-0.033**	-0.037***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Tenure (Yrs)		-0.011***	-0.011***	-0.011***	-0.010***	-0.009***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Schooling (Yrs)			-0.008***	-0.009***	-0.011***	-0.010**
			(0.001)	(0.002)	(0.004)	(0.004)
1(Male)				-0.036***	-0.043***	-0.042***
				(0.011)	(0.011)	(0.011)
Potential Experience					0.005	0.005
					(0.004)	(0.004)
Fixed-effects						
Industry						Yes
Fit statistics						
Observations	4,971	4,892	4,850	4,850	4,843	4,770
Dependent variable mean	0.169	0.165	0.164	0.164	0.164	0.165
R^2	0.002	0.021	0.030	0.033	0.038	0.045

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: All specifications include respondents with valid wage and non-compete status in 2017. The sample further restricts to individuals' main job in 2017. The outcome variable indicates whether a respondent experienced a job separation with their main employer between 2017 and 2019. Potential experience = Age - Highest Educational Grade - 6. There are 17 industries, as reflected in Table 1.

Table A8: Effects of Non-Compete Agreements:
TWFE Results Using an Unbalanced Panel

Dependent Variables:	Log(Wages)	Wage Growth	1(Job Separation)	1(Receipt of Any Training)	1(Employer Pays for Training)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Treated × Years Relative to NC Adoption = -6	-0.047	-0.126**	-0.121***	0.046	0.086***
	(0.043)	(0.053)	(0.031)	(0.039)	(0.033)
Treated × Years Relative to NC Adoption = -4	0.002	-0.022	-0.096***	0.069**	0.061***
	(0.033)	(0.055)	(0.026)	(0.028)	(0.022)
Treated × Years Relative to NC Adoption = 0	0.092***	0.028	-0.101***	0.010	0.019
	(0.034)	(0.054)	(0.024)	(0.021)	(0.017)
Treated × Years Relative to NC Adoption = 2	0.131***	-0.063	-0.057**	-0.002	0.023
	(0.035)	(0.042)	(0.028)	(0.023)	(0.019)
Treated × Years Relative to NC Adoption = 4	0.141***	-0.138***	0.011	-0.011	0.028
	(0.042)	(0.050)	(0.043)	(0.028)	(0.025)
Treated × Years Relative to NC Adoption = 6	0.121**	-0.124**		-0.030	-0.026
	(0.052)	(0.054)		(0.037)	(0.032)
Fixed-effects					
Individual	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	6,918	6,912	5,524	6,918	6,918
Dependent variable mean	3.01	0.100	0.031	0.135	0.104
F-test	682.8	22.3	127.5	128.6	128.6
Number of Individuals	1,444	1,444	1,444	1,444	1,444

Clustered (Individual) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The sample restricts to a unbalanced panel of individuals observed between 2011 and 2019, and who report non-compete status in 2017. Effects are relative to the survey year (two calendar years) prior to the adoption of non-compete agreements. Treated individuals adopt non-compete agreements in 2013, 2015, or 2017. Individuals who are "always-treated" – those that receive treatment before 2011 – are dropped. Individuals without non-compete agreements who do not fall under the "never-treated" category – those without non-compete agreements between 2011-2019 – are also excluded. Standard errors are clustered at the individual level. All columnns are derived from the NLSY97 Public Use Files. Sample sizes vary due to missing values.

Table A9: Effects of Non-Compete Agreements:
TWFE Results Using an Unbalanced Panel and With Industry Controls

Dependent Variables:	Log(Wages)	Wage Growth	1(Job Separation)	1(Receipt of Any Training)	1(Employer Pays for Training)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Treated × Years Relative to NC Adoption = -6	-0.040	-0.119**	-0.116***	0.059	0.095***
	(0.042)	(0.053)	(0.030)	(0.038)	(0.033)
Treated × Years Relative to NC Adoption = -4	9.51×10^{-5}	-0.021	-0.093***	0.074***	0.062***
	(0.033)	(0.054)	(0.026)	(0.028)	(0.022)
Treated × Years Relative to NC Adoption = 0	0.076**	0.009	-0.100***	-0.0003	0.013
	(0.034)	(0.054)	(0.024)	(0.022)	(0.017)
Treated × Years Relative to NC Adoption = 2	0.115***	-0.082*	-0.052*	-0.015	0.014
	(0.035)	(0.042)	(0.028)	(0.023)	(0.019)
Treated × Years Relative to NC Adoption = 4	0.127***	-0.159***	0.013	-0.024	0.018
	(0.042)	(0.050)	(0.042)	(0.028)	(0.026)
Treated × Years Relative to NC Adoption = 6	0.115**	-0.146***		-0.042	-0.033
	(0.051)	(0.055)		(0.037)	(0.033)
Fixed-effects					
Individual	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	6,902	6,896	5,511	6,902	6,902
Dependent variable mean	3.00	0.100	0.031	0.136	0.104
F-test	266.4	9.09	44.2	50.0	49.8
Number of Individuals	1,442	1,442	1,442	1,442	1,442

Clustered (Individual) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The sample restricts to a unbalanced panel of individuals observed between 2011 and 2019, and who report non-compete status in 2017. Effects are relative to the survey year (two calendar years) prior to the adoption of non-compete agreements. Treated individuals adopt non-compete agreements in 2013, 2015, or 2017. Individuals who are “always-treated” – those that receive treatment before 2011 – are dropped. Individuals without non-compete agreements who do not fall under the “never-treated” category – those without non-compete agreements between 2011-2019 – are also excluded. Standard errors are clustered at the individual level. Control variables for industry are included. All columnns are derived from the NLSY97 Public Use Files. Sample sizes vary due to missing values.

Table A10: Effects of Non-Compete Agreements
Using the Never-Treated as a Control Group; Add Control Variables

	Relative Time	Log(Wages)	Wage Growth	1(Job Separation)	1(Any Training)	1(Employer Paid for Training)
	-6	-0.088 (0.051)	-0.137 (0.053)	-0.086 (0.031)	0.046 (0.045)	0.094 (0.035)
	-4	-0.026 (0.042)	-0.014 (0.065)	-0.08 (0.029)	0.066 (0.034)	0.062 (0.028)
	-2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	0	0.195 (0.058)	0.175 (0.102)	-0.095 (0.026)	0.024 (0.03)	0.059 (0.027)
	2	0.255 (0.143)	0.038 (0.167)	-0.08 (0.033)	0.022 (0.035)	0.051 (0.031)
	4	0.126 (0.075)	-0.104 (0.072)	0.025 (0.063)	0.002 (0.041)	0.038 (0.036)
	6	0.078 (0.085)	-0.018 (0.058)		0.038 (0.067)	0.007 (0.061)
N obs		6783	6777	5424	6783	6783
N: Treated		457	457	457	457	457
N: Never Treated		988	988	988	988	988
Dependent Variable Mean		3.005	0.1	0.031	0.135	0.104

Note:
The sample restricts to a unbalanced panel of individuals observed between 2011 and 2019, and who report non-compete status in 2017. Effects using the Callaway and Sant'anna estimator are relative to the survey year (two calendar years) prior to the adoption of non-compete agreements. Treated individuals adopt non-compete agreements in 2013, 2015, or 2017. Individuals who are "always-treated" – those that receive treatment before 2013 – are dropped. Individuals without non-compete agreements who do not fall under the "never-treated" category – those without non-compete agreements between 2011-2019 – are also excluded. Control variables for tenure, sex, and educational attainment are included. Standard errors are clustered at the individual level. All columnns are derived from the NLSY97 Public Use Files. Sample sizes vary due to missing values.

Table A11: Effects of Non-Compete Agreements
Using the Later-Treated as a Control Group

	Relative Time	Log(Wages)	Wage Growth	1(Job Separation)	1(Any Training)	1(Employer Paid for Training)
	-5	-0.021 (0.097)	-0.018 (0.168)	-0.099 (0.059)	0.148 (0.058)	0.11 (0.043)
	-4	0.016 (0.075)	-0.006 (0.122)	-0.067 (0.054)	0.1 (0.053)	0.041 (0.043)
	-3	-0.112 (0.096)	-0.181 (0.119)	-0.037 (0.073)	0.084 (0.055)	0.092 (0.052)
	-2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	-1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	0	0.088 (0.058)	0.01 (0.092)	-0.214 (0.035)	0.094 (0.037)	0.108 (0.028)
	2	0.06 (0.067)	-0.197 (0.077)	-0.222 (0.045)	0.02 (0.05)	0.109 (0.047)
	4	0.216 (0.095)	-0.076 (0.098)	-0.178 (0.08)	-0.005 (0.093)	0.088 (0.07)
N obs		2560	2560	2116	2560	2560
N: Treated		495	495	495	495	495
Dependent Variable Mean		2.907	0.122	0.111	0.139	0.09

Note:
The sample restricts to a unbalanced panel of individuals observed between 2010 and 2019, and who report non-compete status in 2017. Effects using the Callaway and Sant'anna estimator are relative to the survey year (one or two calendar years) prior to the adoption of non-compete agreements. Treated individuals adopt non-compete agreements in 2011, 2013, 2015, or 2017. Only individuals who receive treatment between 2011 and 2017 are included in the sample. Standard errors are clustered at the individual level. All columnns are derived from the NLSY97 Public Use Files. Sample sizes vary due to missing values.