Unlocking Mobility:

Does Banning Non-Compete Agreements Create Shareholder Value?

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Keywords: Non-compete Agreements, Stock Market Reaction, Income Restrictions, Financial Constraints, Volatility, Skilled Labor, Knowledge Intensity

JEL Classification: G14, J08

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Abstract

We examine the stock market reaction to the U.S. Federal Trade Commission's (FTC) 2024 decision to ban non-compete agreements (NCAs) nationwide. Leveraging variation in pre-existing state-level NCA enforceability, we find that firms headquartered in states with stricter enforcement exhibit significantly more positive abnormal returns following the ban. These effects are particularly pronounced in states with income-based NCA restrictions, where the policy meaningfully expands labor mobility for high-skilled workers. Cross-sectional analyses reveal that financially constrained, more volatile, and highly knowledge-intensive firms, which rely heavily on skilled talent to drive innovation, benefit most from the regulatory shift. In contrast, industry leaders that have historically used NCAs to retain human capital and protect their market dominance experience negative abnormal returns, suggesting an erosion of their strategic advantage. Together, our findings highlight how removing legal frictions in labor markets reallocates competitive value from incumbents to challengers, enhancing shareholder value for firms that depend on open access to skilled labor.

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1. Introduction

As a common feature in employment contracts across the United States, non-compete agreements (NCAs) have long been used by firms to restrict employees from working for competitors or starting similar businesses for a specified period after leaving a company, effectively limiting labor mobility (e.g., Marx, Strumsky, and Fleming, 2009; Garmaise, 2011; Starr, Prescott, and Bishara; 2021).[1] However, NCAs have also been criticized for suppressing wages, facilitating monopoly, and stifling innovation, particularly in industries that depend on highly skilled labor (e.g., Marx, 2011; Krueger and Posner, 2018; Starr, Balasubramanian, and Sakakibara, 2018; Starr, 2019; Balasubramanian et al., 2022; Jeffers, 2024).

Specifically, NCAs have been criticized for creating an uneven playing field, especially for young, small, and innovative firms (Jeffers, 2024), as they limit access to specialized professionals with key knowledge and technology. This imbalance is particularly problematic in the age of artificial intelligence (AI), where innovation is a key driver of shareholder value. This study directly addresses a pivotal question: *How does the nationwide ban on NCAs impact shareholder value?* We explore this question by analyzing the stock market's response to the Federal Trade Commission's (FTC) recent landmark decision on April 23, 2024, to ban NCAs nationwide.[2]

The FTC's decision to impose a nationwide ban on NCAs marks one of the most significant shifts in U.S. labor policy in recent decades, offering a unique opportunity to study the impact of labor market regulation on shareholder value. The timing of the vote was not widely anticipated, and the evolving positions of key commissioners added to the uncertainty of its passage—limiting firms' ability to prepare or take preemptive actions. Moreover, the nationwide scope of the ban

[1] Estimates suggest that 38% of U.S. workers have been subject to non-compete agreements at some point in their careers, highlighting their widespread use (Starr, Prescott, and Bishara, 2021).

[2] See https://www.ftc.gov/news-events/news/press-releases/2024/04/ftc-announces-rule-banning-non-competes.

eliminated the possibility of firms strategically relocating to states with more lenient non-compete policies, amplifying the regulatory shock. Aimed at enhancing worker freedom and promoting competition, the ban is expected to have far-reaching implications for firms across the country.

While NCAs have long been a staple of U.S. employment contracts, their legality and enforceability have varied widely across states. For instance, California has historically banned them, whereas states like Washington permit NCAs only for higher-income workers. In many jurisdictions, the enforceability of contracts is determined by courts under broad reasonableness standards. This patchwork of state-level rules has created a complex and fragmented legal landscape, making it difficult to draw clear conclusions about the aggregate effects of NCAs. The FTC's ban thus serves as a compelling natural experiment. Removing NCAs uniformly across all states allows researchers to assess how firms with varying initial exposure to NCA enforcement respond to the same regulatory shock.

This policy change is particularly consequential in the post-COVID-19 economy, where labor market flexibility has become essential for firm adaptability and innovation. Restrictions on employee mobility, such as NCAs, can hinder firms' ability to hire and retain skilled talent—especially in high-skill industries. By eliminating these restrictions, the FTC's decision is expected to facilitate more efficient talent reallocation, boost innovation, and reduce hiring frictions. These effects are likely to be most pronounced for smaller, financially constrained, or volatile firms that face greater obstacles in securing high-skilled labor (Jeffers, 2024).

To empirically examine the implications of the ban, we analyze stock price reactions to the FTC's announcement on April 23, 2024. Using daily stock return data, we find that firms located in states that previously enforced NCAs experienced significantly positive abnormal returns in the days surrounding the announcement. This suggests that investors expect improved firm performance due to increased labor mobility and associated productivity gains. Importantly, the magnitude of the stock market reaction varies systematically with firm and state characteristics. In particular, firms located in states that enforced NCAs for higher-income skilled workers exhibited the strongest positive responses—outperforming firms in states that had already banned NCAs by more than 1 percentage point over the seven-day event window.[3]

This finding suggests that investors expect these firms to benefit from the newfound ability to attract and retain key skilled talent without the constraints of non-compete agreements. To ensure the robustness of our findings, we conduct a placebo test by randomly reassigning each firm's pre-FTC state-level non-compete restriction based on its actual sample probability distribution and then reestimating the regression using 1,000 bootstrapped pseudo samples. The results show that our findings are unlikely to be driven by random forces.

Further cross-sectional analyses reveal that the market's response to the FTC's non-compete ban is strongly shaped by firm-specific characteristics that govern the value of enhanced labor mobility. We find that financially constrained and riskier firms—often younger, smaller, and more resource-limited—exhibit significantly stronger positive stock price reactions. These firms frequently operate at a disadvantage under NCA regimes, struggling to compete for skilled talent against well-capitalized incumbents. By removing legal barriers that restricted access to human capital, the FTC's ban unlocks growth potential for these firms, enabling them to recruit, innovate, and scale more effectively. This result is consistent with Jeffers (2024), who argues that NCAs entrench incumbent advantages and systematically disadvantage challengers.

[3] Note the FTC's ban would not exert any additional shock to firms in states where NCAs were already banned (i.e., the "Full Ban" group). Thus, we use the "Full Ban" group as the reference group and measure the marginal impact on stock market reactions for the other groups.

Knowledge-intensive firms—identified through high R&D and SG&A investment or high-tech industry classification—also experience notably positive market reactions. These firms rely heavily on specialized human capital as the engine of innovation and long-term value creation. In such contexts, labor is not just an input—it is a strategic asset. By enhancing mobility, the FTC's ban expands these firms' access to critical talent pools, amplifying their capacity to generate intangible capital and drive technological progress. The policy is thus seen by investors as expanding the innovation frontier for firms previously constrained by labor frictions.

We further examine the role of skilled labor dependence, which serves as the key mechanism through which the ban creates value. Firms with high exposure to skilled labor risk (Qiu and Wang, 2021) or heavy reliance on specialized employees (Belo et al., 2017) show stronger positive responses—consistent with the view that the relaxation of mobility constraints improves strategic human capital allocation. These findings reinforce the idea that the gains from the FTC's ban are driven by increased access to high-value labor, particularly in sectors where talent is central to productivity and competitive positioning.

In contrast, dominant industry leaders—defined as the top 1% of firms by market share—react negatively to the ban. These firms have historically used non-compete agreements to retain key personnel and insulate themselves from talent-driven competition. By eliminating this structural advantage, the FTC's policy rebalances competitive dynamics, empowering challengers and diminishing incumbents' ability to defend their market position through contractual restraints. The stock market's reaction reflects this shift: while financially weaker, knowledge-dependent firms gain from newly available talent, entrenched leaders lose a critical mechanism for defending their dominance. This contrast underscores the broader economic implications of the ban—not just as a labor market reform, but as a catalyst for competitive renewal in the knowledge economy.

Thus, our results indicate that the FTC's non-compete ban has, on average, created shareholder value—particularly in states that previously enforced NCAs for higher-income, skilled employees. The positive market response is likely driven by improved access to specialized talent, which enhances labor market flexibility and unlocks firm-level innovation potential. These gains are especially concentrated among firms that are financially constrained, more volatile, or heavily dependent on human capital and knowledge-based resources for growth.

By leveling the playing field and expanding access to a broader pool of skilled workers, the FTC's reform reshapes the competitive landscape—empowering challengers and eroding structural advantages previously held by dominant incumbents. Our findings remain robust across a range of empirical specifications, including controls for local labor regulations and economic conditions, alternative standard error clustering methods, bootstrapping procedures, and broader firm samples using different measures of NCA enforceability.

This study makes several contributions to the literature. First, it enriches the growing body of research on the economic effects of labor market regulations, particularly the role of NCAs in shaping firm outcomes (e.g., Marx, Strumsky, and Fleming, 2009; Garmaise, 2011; Starr, Balasubramanian, and Sakakibara, 2018; Balasubramanian et al., 2022; Jeffers, 2024). While prior studies have primarily focused on how NCAs influence wages, employee mobility, and investment decisions, this paper shifts the focus to capital markets. By analyzing stock market responses to the FTC's nationwide ban, we offer new insights into how investors interpret and price the strategic implications of labor mobility reforms. Shareholder value, as a forward-looking metric, captures market expectations about how the ban will affect firms' future cash flows, competitive positioning, and exposure to talent-related risks.

Second, the study contributes to the literature on how state-level regulatory heterogeneity shapes firm behavior and performance (e.g., Autor, Donohue, and Schwab, 2004; Acharya, Baghai, and Subramanian, 2014; Serfling, 2016; Klasa et al., 2018; Qiu and Wang, 2018). The FTC's ban, imposed uniformly across states, offers a rare natural experiment to assess how firms previously subject to different levels of NCA enforceability react to the harmonization of labor policy. Our cross-state analysis highlights the importance of legal and institutional frictions in mediating the economic consequences of regulatory change—an insight of growing relevance to ongoing debates over the balance of federal and state authority in labor markets.

Third, this study contributes to the literature on corporate strategy and competitive advantage by showing how labor market regulation shapes firms' access to human capital—a critical input for innovation and growth. Our findings that the ban disproportionately benefits firms that are more reliant on skilled labor and knowledge intensity underscore the strategic value of talent mobility. These results suggest that in an era increasingly defined by artificial intelligence and knowledge-based production, regulatory shifts that enhance labor flexibility can significantly affect competitive dynamics and value creation.

The rest of the paper is organized as follows. Section 2 discusses the institutional background, data, sample, and variables. Section 3 presents the findings on stock price reactions to the FTC's ban on non-compete agreements. Section 4 reports the results of additional robustness tests. Section 5 provides concluding remarks. The Online Appendix includes variable definitions, the status of non-compete agreement enforcement by states prior to the FTC's nationwide ban on non-competes, and additional empirical results.

2. Background and Data

2.1 Use of Non-Compete Covenant in the United States

Non-compete agreements (or non-compete covenants) have been a significant feature of the United States labor market for over a century. These covenants are contractual agreements that restrict an employee's ability to work for competitors or start a similar business for a certain period and within a specific geographic area after leaving an employer. The primary purpose is to protect trade secrets, prevent unfair competition, and safeguard investments in employee training. However, the enforcement and regulation of NCAs in the United States have varied considerably across states, reflecting diverse legal traditions, economic policies, and labor market conditions.

The legal landscape for NCAs is highly fragmented, with each state adopting its own approach. Some states, such as California, have taken a stringent stance against NCAs. California's law, under Business and Professions Code Section § 16600, renders almost all NCAs unenforceable, reflecting the state's strong public policy favoring open competition and employee mobility (Marx, Strumsky, and Fleming, 2009). This strict prohibition has played a significant role in the growth of Silicon Valley, where the free movement of talent has been a key driver of technology innovation.

In contrast, many other states, such as Michigan and North Carolina, have enforced NCAs through judicial interpretation based on reasonableness standards, allowing greater discretion in determining enforceability. In these states, courts have upheld NCAs that protect legitimate business interests, such as trade secrets, customer relationships, and specialized training investments, while also ensuring that the restrictions are not overly broad or oppressive to employees (Balasubramanian et al., 2022). For instance, Florida's Statute § 542.335 allows for the enforcement of NCAs if they are reasonable in terms of duration, geographic area, and the line of business protected, and if they are necessary to protect the employer's legitimate business interests.

Many states occupy a middle ground, balancing the interests of employers and employees. For example, Illinois and Massachusetts enforce NCAs but have introduced statutory reforms to curb potential abuses. Illinois' Freedom to Work Act, which went into effect in January 2022, prohibits non-compete agreements for employees earning below a certain wage threshold, while Massachusetts' Non-competition Agreement Act of 2018 limits the enforceability of non-compete agreements to specific scenarios and mandates that employers provide "garden leave" or other compensation during the non-compete period (Starr, Balasubramanian, and Sakakibara, 2018).

The patchwork of state laws regarding NCAs has significant implications for labor mobility, wage growth, and innovation. In states with strict enforcement of NCAs, employees often face greater difficulty in changing jobs, which can lead to suppressed wages and reduced career opportunities (Krueger and Posner, 2018). These restrictions can also stifle innovation by limiting the free flow of knowledge and skills between firms, particularly in industries that rely heavily on human capital and specialized expertise. Conversely, states that restrict or prohibit NCAs, like California, tend to have more dynamic labor markets with higher rates of entrepreneurship and innovation.

2.2 The Federal Trade Commission's Ban on Non-Compete Agreements

The rise of the knowledge economy and the increasing importance of intellectual property have led many firms to rely more heavily on NCAs to protect their intangible assets. At the same time, there has been growing recognition of the negative impacts of these agreements on workers and the economy as a whole. This has led to a wave of legal reforms at the state level aimed at curbing the use of NCAs, particularly for low-wage workers and in industries where they are deemed unnecessary or harmful (Starr, 2019).

The Federal Trade Commission (FTC)'s decision to ban NCAs nationwide followed years of rising concern about the effects these agreements had on workers and the economy. Originally, NCAs were used to protect employers' interests by preventing former employees from joining competitors or starting similar businesses. However, the scope of their application gradually expanded, raising alarms as studies showed that NCAs restricted wages, limited job mobility, and constrained innovation (e.g., Marx, 2011; Krueger and Posner, 2018; Starr, Balasubramanian, and Sakakibara, 2018; Starr, 2019; Balasubramanian et al., 2022; Lipsitz and Starr, 2022). For example, Lipsitz and Starr (2022) show that the 2008 Oregon ban on NCAs for hourly-paid workers significantly increased their hourly wages.

At the federal level, the movement to restrict NCAs gained momentum in 2021 when President Joe Biden issued an executive order encouraging the FTC to investigate and limit their use.[4] The order reflected growing dissatisfaction with NCAs, particularly their detrimental effects on labor markets and wage growth. Several states, such as Illinois and Massachusetts, had already enacted reforms to regulate the use of NCAs. Nevertheless, the enforceability of NCAs remained inconsistent across states in the U.S., contributing to a fragmented legal landscape that underscored the need for federal intervention.

According to the Economic Innovation Group's State Non-Compete Law Tracker,[5] all states can be categorized into four groups based on how they regulated non-compete agreements prior to the FTC's nationwide ban. Full Ban states, such as California, completely prohibited the use of non-compete agreements in employment contexts, fostering greater labor mobility. Income Restrictions states, like Illinois, allowed non-competes only for employees earning above a

[4] See https://www.whitehouse.gov/briefing-room/statements-releases/2021/07/09/fact-sheet-executive-order-on-promoting-competition-in-the-american-economy/.

[5] See https://eig.org/state-noncompete-map/.

specified income threshold. Other Restrictions states, such as Massachusetts, imposed additional limitations, including restrictions on the duration of non-competes or their applicability within certain industries. Lastly, Court Discretion states, such as Pennsylvania, lacked specific legislation governing NCAs; instead, the enforceability of these agreements was left to the courts, which ruled based on the "reasonableness" of the restrictions. This patchwork of legal approaches highlights the fragmented regulatory environment that ultimately necessitated a more uniform federal policy. Figure 1 maps the states into these four categories.

[Please Insert Figure 1 here]

Table 1 summarizes the most recent statutory restrictions on NCAs in each state at the end of March 2024 prior to the April 2024 FTC's nationwide announcement banning NCAs. Table A2 in the Online Appendix further provides detailed explanations of each state's most recent updates to its non-compete statutes in March 2024 before the FTC's nationwide ban in the following month.

[Please insert Table 1 here]

In January 2023, the FTC formally proposed a nationwide ban on NCAs in response to these concerns.[6] Chair Lina M. Khan, a strong advocate for labor market reforms, led the charge in framing the ban as essential for protecting workers' rights and fostering economic competition. The proposal drew upon extensive public consultations, with input from workers' advocacy groups, legal scholars, and economists. Proponents of the rule underscored the harmful impact of NCAs on wage growth and labor mobility, while business groups voiced concerns over how a blanket ban could hinder their ability to protect trade secrets and client relationships.

The debate among the FTC commissioners reflected these tensions. While Chair Khan and Commissioner Rebecca Kelly Slaughter were early supporters of the ban, Commissioner Alvaro

[6] See https://www.ftc.gov/news-events/news/press-releases/2023/01/ftc-proposes-rule-ban-noncompete-clauses-which-hurt-workers-harm-competition.

M. Bedoya initially expressed hesitation. Bedoya's concerns centered on whether a broad ban was appropriate, especially for high-income earners, and whether such a rule should be implemented through regulation rather than case-by-case enforcement. However, after extensive deliberation and a reassessment of the wider economic impacts, Bedoya ultimately voted in favor of the rule. His changing view was pivotal, securing a 3-2 vote alongside Khan and Slaughter. Dissenting commissioners Melissa Holyoak and Andrew N. Ferguson argued that the rule was overreaching and could have unintended negative consequences for certain industries.

The FTC's decision to implement a nationwide ban on NCAs marked a significant regulatory shift and an exogenous shock to firms located in different states. The timing of the vote was not widely anticipated, and Bedoya's evolving stance only heightened the unpredictability of the passage of the FTC's ban. This lack of clarity made it difficult for firms to foresee the outcome or take preemptive action. Furthermore, the nationwide scope of the ban prevented firms from strategically relocating to states with more lenient non-compete policies, amplifying the unanticipated nature of the regulatory change. This exogenous shock to labor market regulations thus provides a unique, ideal opportunity to study how removing NCAs affects firm stock prices, particularly in industries reliant on skilled labor and innovation.

The FTC's recent decision to ban NCAs nationwide reflects a growing consensus that, while these agreements may serve to protect business interests, they often inflict more harm than good by limiting labor mobility, suppressing wages, and stifling innovation. We expect the FTC's ban on NCAs to have significant implications for labor markets across the United States, creating a more equitable environment for workers and promoting a more dynamic and competitive economy in the current era of AI and innovation. Thus, we anticipate positive stock price reactions for firms in states where non-competes were previously enforced. These positive market responses are likely to be especially pronounced for firms that stand to benefit most from the FTC's ban, particularly young and small-sized firms facing significant financial constraints, heightened volatility, and/or greater dependence on skilled labor and knowledge-intensive operations.

2.3 Data, Sample and Variables

To analyze the stock market reactions, we obtain daily stock price data of all common stocks (CRSP share codes 10 or 11) listed on NYSE, AMEX, and NASDAQ from the Center for Research in Security Prices (CRSP). We measure firms' buy-and-hold stock returns as individual firms' daily compounding returns. For robustness, we also calculate firms' cumulative abnormal stock returns using the market-adjusted model. We use the S&P 500 stock market index as the market portfolio. The market-adjusted model calculates daily abnormal stock returns by subtracting the actual market returns from the individual stock returns. We calculate both the 7-day (from -3 to +3) and 5-day (from -2 to +2) buy-and-hold stock returns (BHRs) and cumulative abnormal stock returns (CARs) for all firms around the FTC's nationwide non-compete ban announcement.

A key component of our empirical strategy involves linking firms' stock price reactions to the pre-ban non-compete agreement (NCA) rule statuses of the states in which their headquarters are located. This approach enables us to explore cross-sectional variations in market responses to the FTC's nationwide policy shock. While publicly traded firms often operate across multiple states or countries, the headquarters state typically anchors strategic decision-making—especially in areas like human capital management, legal compliance, and corporate governance. As such, investors are likely to assess the implications of a federal policy shift based on the regulatory environment at the firm's strategic center. Despite geographic dispersion, core corporate decisions related to labor policy and the use of NCAs tend to reflect the legal regime at headquarters, which shapes the firm's overarching approach to employment contracting. Consequently, stock market reactions reflect investors' evaluations of how the federal ban interacts with the firm's primary regulatory context.

To control for firm characteristics, we obtain one-quarter-lagged financial data from Compustat. We include standard firm-level control variables, such as firm size (*Size*), profitability (*ROA*), market-to-book equity ratio (*MTB*), leverage ratio (*Leverage*), past stock returns (*Past Return*), past return volatility (*Vol*), and illiquidity (*Illiquidity*), as these firm characteristics are known to be related to cross-sectional stock returns.

Our dataset consists of 2,839 firm observations with non-missing stock returns and financial data. Table A1 in the Online Appendix provides the detailed definition and data source for each of the variables used in the study and Table 2 provides the summary statistics. All continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of outliers.

[Please insert Table 2 here]

3. The Effects of the FTC's Non-Compete Ban

In this section, we first examine how the stock returns of firms located in states with varying NCA enforcement statuses prior to the nationwide ban react to the FTC's announcement. Next, we explore firm heterogeneity and investigate whether different firm characteristics and local labor market conditions further mitigate or amplify the effects of the FTC's ban.

3.1. Stock Price Reactions to the FTC's Non-Compete Ban

We begin by examining how the stock returns of firms in states with varying levels of NCA enforcement prior to the ban respond to the FTC's announcement. Although the FTC's ban applies uniformly to firms across all states, its impact varies depending on each state's previous NCA enforcement conditions. For example, to protect low- to mid-level income workers and support the labor mobility essential for economic vitality, some states restrict NCAs to contracts for professional workers above a certain income threshold. The FTC's ban effectively removes this "income threshold" by prohibiting NCAs for all workers, regardless of income level. Consequently, we interpret the FTC's ban as an "income-restriction ban" for states that previously enforced NCAs with income limits.

To capture this variation, we classify states' responses to the ban into the following categories: Income Restrictions, Other Restrictions, and Court Discretion. Note that the FTC's ban introduces no additional impact for firms in states where NCAs were already fully banned (the Full Ban group). We use this group as the reference group in our analysis.[7] We then regress stock returns on these three variables, estimating the following regression model:

$$\begin{aligned} Return_i = \alpha + \beta_1 Income\ Restrictions_i + \beta_2 Other\ Restrictions_i \\ + \beta_3 Court\ Discretion_i + \beta_4 Controls_i + Industry\ FE + \varepsilon_i . \end{aligned} \quad (1)$$

In Equation (1), the dependent variable, *Return*, is the buy-and-hold stock return (BHR) of firm *i*. *Income Restrictions* equals 1 if firm *i* is located in a state that, prior to the FTC's ban, had statutes limiting the use of NCAs to cases where workers' incomes exceeded certain thresholds, and equals 0 otherwise. This variable essentially captures the effects of removing restrictions on the mobility of higher-income workers for local firms. *Other Restrictions* equals 1 if firm *i* is located in a state that imposed other limitations, such as restrictions on the duration of NCAs or their applicability within certain industries before the FTC's ban, and equals 0 otherwise. *Court*

[7] Table A3 in the Online Appendix presents 7-day buy-and-hold stock returns (BHRs) for firms headquartered in states with Full Ban, Income Restrictions, Other Restrictions, and Court Discretion on non-competes, measured around the FTC's non-compete ban proposal date of January 5, 2023. The table reports the mean BHRs for each category, along with the differences in means between Income Restrictions, Other Restrictions, and Court Discretion relative to Full Ban, as well as the corresponding *t*-values. Our analysis reveals that these differences in means are all statistically insignificant, suggesting that the FTC's initial proposal did not elicit divergent stock return reactions across the various groups. This outcome is likely attributable to the high uncertainty surrounding whether the proposal would gain sufficient support for adoption at that time.

Discretion equals 1 if firm *i* is located in a state where the NCA enforceability is left to the courts, which rule based on the "reasonableness" of the NCAs and equals 0 otherwise.

As discussed earlier, we control for firm size (*Size*), profitability (*ROA*), market-to-book equity ratio (*MTB*), financial leverage (*Leverage*), past stock returns (*Past Return*), stock return volatility (*Vol*), and stock illiquidity (*Illiquidity*). We also include industry fixed effects (2-digit SIC) to control for time-invariant industry characteristics that may influence stock price reactions to the FTC's ban. Since firms within the same state are subject to the same statutory restrictions regarding NCA enforcement, they experience similar shocks following the FTC's ban. Consequently, their stock returns may exhibit co-movement during the event period. To address this potential issue, we cluster the standard errors at the firms' headquarters state level. The results are reported in Table 3.

[Please insert Table 3 here]

Using alternative regression specifications across columns (1)–(4) in Table 3, we find that the FTC's nationwide non-compete ban has a significant positive impact on firms' stock returns across states. Specifically, relative to firms located in the Full Ban states, the nationwide NCA ban has led to an incremental increase of approximately 0.1 to 1.9 percentage points in firms' stock returns over a 7-day event window for firms located in states where NCAs were previously enforceable to varying degrees.

Interestingly, the magnitude and statistical significance of the increase in buy-and-hold stock returns depend on the type of shock introduced by the FTC's ban. Notably, we observe the strongest response from firms located in states where NCAs were previously enforceable for higher-income employees. On average, the FTC's ban on NCAs leads to an increase in BHRs by 1.2 to 1.9 percentage points in these states. The economic impact is substantial: for an average firm in these states, with a market capitalization of $16.498 billion in our sample, the FTC's ban on NCAs translates to an increase in shareholder value of approximately $197.98 million to $313.46 million over the 7-day event window.

These results indicate that, on average, shareholders favor the removal of mobility restrictions on higher-income employees, suggesting that the expected increase in job mobility among these skilled professionals may enhance firms' productivity and market value. In today's fast-paced technological and AI-driven era, the restrictive effects of NCAs on skilled labor mobility can stifle innovation and limit a firm's capacity to adapt to evolving market conditions. The impact of the FTC's ban on NCAs is particularly pronounced in Income Restrictions states, where the ban lifts constraints on the mobility of skilled talent—an essential factor for maintaining competitive productivity and innovation. This is especially relevant in the post-COVID-19 tight labor market, where optimal matching between firms and skilled talent is crucial. The NCA ban thus contributes to a notable increase in firms' market value in these states. Interestingly, for firms located in states that imposed other types of NCA restrictions or where NCA enforcement was previously subject to court discretion, the increases in stock returns are positive on average but are statistically insignificant, suggesting that the most substantial benefits arise specifically from increased mobility of higher-compensated skilled professionals.

To examine cross-state variations in market responses, Figure 2 plots the 7-day buy-and-hold stock returns of firms located in states with different NCA regimes—specifically, Income Restrictions, Court Discretion, and Other Restrictions—relative to those in Full Ban states, which serve as the benchmark. All three groups experience positive returns relative to the Full Ban group following the FTC's nationwide ban announcement. The strongest positive reaction is observed among firms located in Income Restrictions states, followed by firms located in Court Discretion and then Other Restrictions states. These patterns suggest that the regulatory change is viewed more favorably by markets in states that previously enforced NCAs more stringently for higher-income employees.

[Please Insert Figure 2 here]

To ensure the robustness of our findings, we randomly reassign each sample firm's headquarters state statutory restriction on non-competes—prior to the FTC's nationwide ban—to one of four categories (Full Ban, Income Restrictions, Other Restrictions, or Court Discretion) based on their actual sample probability distribution. This process is repeated 1,000 times to generate 1,000 pseudo samples, which we then use to reestimate the regression specification from Table 3, column (4). Table 4 presents the summary statistics for the regression coefficient estimates derived from these 1,000 bootstrapped samples, reporting the mean, standard deviation, *t*-values, minimum, maximum, and percentile distributions.

[Please insert Table 4 here]

The results in Table 4 show that the mean coefficient estimates of the *Income Restrictions*, *Other Restrictions*, and *Court Discretion* indicators are all close to zero using the bootstrapped pseudo samples, with *t*-values ranging from 0.02 to 0.08. Notably, the maximum coefficient estimate of *Income Restrictions* across the 1,000 regressions is 1.134, whereas the coefficient estimate of *Income Restrictions* obtained from our actual sample is 1.268. These findings suggest that our results are robust and unlikely to be driven by random forces.

Figure 3 plots the frequency histograms and probability density function of the regression coefficient estimates for the *Income Restrictions* indicator, derived from 1,000 bootstrapped pseudo samples. The vertical dotted line in the middle represents the mean (0.006) of these bootstrapped pseudo coefficient estimates, while the vertical solid line on the right marks the actual coefficient estimate (1.268). The distribution of pseudo coefficient estimates is approximately normal and centered around zero, whereas the actual coefficient estimate lies beyond the range of this distribution, highlighting its statistical significance.

[Please insert Figure 3 here]

We further use the 7-day cumulative abnormal stock returns (CARs) as the dependent variable and re-estimate Equation (1). The results are reported in Table A4 in the Online Appendix. The coefficient estimate of *Income Restrictions* is again positive across all regression specifications and statistically significant at the 1% level, indicating a positive impact on firms' cumulative abnormal stock returns across Income Restrictions states around the FTC's nationwide non-compete ban. Results are qualitatively similar to the baseline regression results reported in Table 3. Additionally, we use an alternative 5-day event window to calculate firms' BHRs and CARs, respectively, and results are again qualitatively similar to the baseline results (see Tables A5 and A6 in the Online Appendix). These results confirm a profound positive impact on firms' stock returns across all Income Restrictions states after the FTC's nationwide non-compete ban.

3.2 Heterogeneous Effects of the FTC's Non-Compete Ban across Firms

The core premise underlying the heterogeneous effects is that the FTC ban's impact is most pronounced where the change in enforceability is most significant and directly affects the most valuable talent pool. In Income Restrictions states, NCAs were previously enforceable specifically for higher-income, skilled employees, who are precisely the critical human capital for knowledge-intensive, innovative, and financially constrained firms. The ban directly liberates this specific, high-value segment of the labor force in these states, creating a "shock" that is most acutely felt and valued by firms that rely on this talent. This direct and targeted impact leads to the most significant market re-evaluation. In contrast, in Full Ban states like California, skilled labor mobility was already high due to pre-existing bans, meaning the FTC ban introduced no additional change in their ability to acquire or retain skilled labor through NCAs. Consequently, firms here would experience minimal incremental benefit from the ban, serving as a baseline. For Other Restrictions and Court Discretion states, while some level of NCA enforceability existed, the restrictions might have been less stringent or not specifically tied to the income of skilled professionals, leading to a less pronounced impact compared to the clear and direct liberation of high-value talent in Income Restrictions states. The heterogeneity analyses thus focus on the incremental impact of the ban, with the largest incremental benefits expected where the ban causes the largest marginal change in the availability of the most impactful type of labor.

3.2.1 Firm Financial Profiles

We begin with firm financial profiles, as these determine which firms are most constrained in accessing skilled talent and hence stand to benefit most from the removal of non-compete restrictions. As Jeffers (2024) argues, the enforcement of NCAs restricts the mobility of knowledge employees, thereby disproportionately harming smaller and younger firms, which are typically more financially constrained and riskier. The FTC's non-compete ban generally led to positive stock returns for firms located in states that previously enforced NCAs. Does this benefit primarily accrue to smaller, financially weaker firms, or to larger, more established firms and industry giants? This section investigates how firm financial profiles moderate stock market responses to the ban.

In the context of the FTC's non-compete ban, we expect that smaller, younger firms with weaker financial profiles stand to benefit disproportionately. By lifting restrictions on skilled labor mobility, the ban helps level the playing field, allowing these firms to compete more effectively with larger, established competitors. Freed from the barriers of non-compete agreements, smaller, younger firms can attract key talent previously out of reach, leveraging these new human resources to drive growth and innovation. This shift not only improves their competitive stance but also translates to stronger positive stock returns as the market recognizes their enhanced potential.

While publicly listed firms, even those categorized as "small" or "young" within the sample, generally possess greater access to capital and labor markets compared to unlisted startups, they still face comparatively higher financial constraints and perceived risk than large, established public firms. Their growth trajectories are often more sensitive to the availability of specialized human capital. For financially constrained or riskier public firms, access to critical human capital can represent a significant binding constraint on their growth options and innovation potential. When this constraint is relaxed by the NCA ban, the market perceives a substantial increase in their future growth opportunities and a reduction in the risk associated with talent acquisition. This directly translates into a higher valuation. For less constrained firms, this constraint was less binding, so the marginal benefit of its removal is comparatively smaller, leading to a more muted market response.

To this end, we employ a range of measures to capture firms' financial constraints and risk profiles. These include the Hadlock-Pierce size-age (*HP*) index, Kaplan-Zingales (*KZ*) index, and Whited-Wu (*WW*) index, which are widely recognized in the literature for assessing financial constraints. Additionally, we consider dividend distribution status and utilize machine-learning-enhanced text-based measures for equity and debt constraints (*LW Equity Constraint* and *LW Debt Constraint*) (Linn and Weagley, 2024).[8] For risk assessment, we use Altman's Z-Score (*Z-Score*),

[8] The equity and debt constraint measures developed by Linn and Weagley (2023) are machine-learning extensions of the text-based financial constraint measures introduced by Hoberg and Maksimovic (2015), which identify direct statements indicating financial constraints. Linn and Weagley (2023) employ a random forests algorithm to estimate a multidimensional relationship between firm-level accounting variables and financial constraints. We use their equity- and debt-focused constraint measures, calculated using the more rigorous "Exogenous" model.

a widely recognized measure of firm risk and bankruptcy potential. The results are reported in Table 5.

[Please Insert Table 5 Here]

Our subsample analysis reveals that smaller, younger, financially constrained, and riskier firms exhibit significantly stronger positive stock returns following the FTC's non-compete ban. Specifically, firms with higher *HP*, *KZ*, and *WW* indices—indicating greater financial constraints—benefit more from the FTC's ban. For instance, the coefficient estimates for *Income Restrictions* are large in magnitude and statistically significant at the 1% level for the subsample of financially constrained firms. In contrast, the coefficient estimates for *Income Restrictions* are smaller in magnitude and less significant, or even insignificant, for firms facing more relaxed financial constraints. Similarly, firms that do not distribute dividends and those identified as more equity- and debt-constrained based on the machine-learning-enhanced text-based measures (i.e., *LW Equity Constraint* and *LW Debt Constraint*), also experience more pronounced positive stock returns. These results align with our hypothesis and Jeffers' (2019) findings, suggesting that smaller, younger, and more financially constrained firms benefit more from the FTC's non-compete ban.

Further examination of riskier firms, as indicated by lower Altman's Z-Scores, reveals a similar pattern. These firms, closer to financial distress, also experience significantly positive stock returns around the FTC's ban announcement. This result is particularly intriguing, as it suggests that the market perceives the policy change as a potential lifeline for firms struggling to acquire skilled labor and seen as vulnerable due to their financial and operational profiles.

The stronger response from financially constrained and riskier firms can be attributed to their higher marginal value of accessing skilled labor. These firms often struggle more to attract and retain skilled talent due to financial constraints and perceived risk. The FTC's ban on NCAs effectively lowers these barriers, enabling them to tap into a more mobile and accessible pool of skilled workers. This increased access to talent is likely perceived by investors as a meaningful competitive advantage, leading to more substantial stock price appreciation.

Next, we extend our analysis to explore the role of firm volatility in shaping stock price responses to this policy change. Given the inherent risk associated with volatile firms, we expect that these firms may similarly experience stronger positive effects from the removal of the non-compete restrictions. In particular, we employ several measures of firm volatility, including stock price volatility (*Vol*), return on assets volatility (*Roa Vol*), cash flow volatility (*Cash Flow Vol*), and idiosyncratic volatility (*Ivol*). These measures collectively capture different dimensions of a firm's risk profile, from its financial performance to its market behavior. Results are summarized in Table 6.

[Please Insert Table 6 Here]

Our results indicate that the positive effects of the FTC's non-compete ban on stock returns are indeed more pronounced for high-volatility firms. Firms with higher *Vol*, *Roa Vol*, *Cash Flow Vol*, and/or *Ivol* exhibit stronger positive stock price reactions around the FTC's ban. This finding is consistent with the pattern observed in our earlier analysis, where smaller, younger, riskier, and financially constrained firms were shown to benefit more from the ban.

Like smaller, younger, and financially constrained firms, high-volatility firms operate in environments with greater uncertainty and often face challenges in recruiting skilled talent. For instance, many young startups or tech firms listed on the NASDAQ have significantly higher risks. When competing with industry giants such as Microsoft or Pfizer, which previously retained a significant share of skilled talent through non-compete agreements, these high-volatility firms are at a disadvantage in pursuing innovation-driven growth due to limited access to industry skilled talent. The FTC's ban on NCAs likely provides these firms with a crucial advantage—greater access to skilled labor—which, in turn, enhances their potential for growth and innovation. This benefit is particularly impactful for firms whose business models are highly sensitive to fluctuations in market conditions, financial performance, or operational cash flows.

In contrast, firms with lower volatility, generally perceived as more stable and less risky, do not experience as significant a boost from the FTC's policy change. These firms rely less on regulatory shifts to attract and retain skilled talent, as their stability and lower risk profiles already allow them to retain a large number of skilled workers. Consequently, the removal of NCAs does not drastically alter their competitive position or their capacity for innovation, resulting in a more muted stock price response.

3.2.2 Firm Knowledge Intensity

We next examine knowledge-intensive firms, which are particularly sensitive to changes in access to specialized labor. These firms derive much of their value from intangible assets and human capital, making them likely beneficiaries of enhanced labor mobility. If the FTC's non-compete ban facilitates the freer movement of skilled professionals, we expect such firms to exhibit more pronounced positive stock price reactions.

A firm's knowledge intensity—reflected in its investment in research and development, innovation capacity, and reliance on a specialized labor force—plays a central role in shaping its response to the FTC's ban. Specifically, firms with higher knowledge intensity are more likely to benefit from the increased availability of skilled talent, which is a critical input for innovation and competitive advantage.

To test this prediction, we examine the differential stock price reactions of firms with varying levels of knowledge intensity. Following the literature, we proxy knowledge intensity using firm-level Selling, General, and Administrative (SG&A) expenses, firm-level R&D expenditures, industry-level averages of SG&A and R&D expenses (based on 3-digit SIC codes), and high-tech industry classification. We assess whether firms with higher SG&A or R&D spending, or those operating in high-tech sectors, experience stronger positive market reactions to the FTC's non-compete ban. The results are reported in Table 7.

[Please Insert Table 7 Here]

Comparing columns (1) and (2), we find that firms with higher SG&A expenses, which often indicate substantial investment in knowledge-based resources, exhibit a significant amplification in positive stock returns following the FTC's non-compete ban. Numerous studies (e.g., Lev and Radhakrishnan, 2005; Lev, Radhakrishnan, and Zhang, 2009; Banker, Huang, and Natarajan, 2011; Eisfeldt and Papanikolaou, 2013; Li, Qiu, and Shen, 2018) have validated SG&A expense as an effective proxy for a firm's organizational capital—an accumulation of proprietary knowledge, including operational processes and know-how, that generates a competitive edge and is difficult for competitors to replicate (Prescott and Visscher, 1980).[9] As a result, firms that rely more heavily on organizational capital are likely to experience a boost as the restrictions on higher-income professionals' mobility are lifted, enhancing their ability to acquire key skilled talent and maintain a competitive advantage.

Consistently, firms with higher R&D spending, reflecting robust innovation capacity, are more positively impacted by the FTC's regulatory change. Higher R&D expenditure is a key

[9] SG&A expenses include R&D expenses (Compustat Manual) and a majority of Compustat firm-year observations have valid (i.e., non-missing) information on SG&A expenses. By contrast, a majority of firms do not separately report R&D expenses.

indicator of a firm's knowledge intensity and potential for innovation. The FTC's non-compete ban likely benefits these highly innovative firms by improving their access to specialized professionals with production-relevant knowledge and expertise. Consequently, firms with greater R&D spending experience a stronger positive impact on their stock returns, reflecting the enhanced prospects of acquiring valuable human capital (columns (3) and (4)).[10] We further examine the heterogeneous effects of the FTC's rule change across firms in industries with high vs. low SG&A and R&D spending. Consistent with the findings on firm-level SG&A and R&D expenses, the results in columns (5)-(8) show that firms in industries with higher SG&A or R&D spending experience more positive stock returns. Lastly, high-tech firms, known for their reliance on specialized knowledge and innovation, exhibit similar patterns. Firms in high-tech industries are more likely to benefit from the FTC's non-compete ban, resulting in a more pronounced effect on their stock returns (columns (9) and (10)).

In sum, our findings align with the broader literature on labor mobility and firm dynamics, reinforcing the notion that smaller, younger, riskier, and financially constrained firms benefit most from regulatory changes that enhance labor market flexibility (e.g., Jeffers, 2019). Our results indicate that, by relaxing restrictions on skilled labor mobility, the FTC's non-compete ban may have leveled the playing field, allowing these firms to compete more effectively for skilled talent and strengthen their market position.

3.2.3 Labor Frictions

We then turn to labor frictions—the core mechanism through which firms capitalize on the FTC's regulatory change. The benefits of the non-compete ban should be most pronounced for firms that rely heavily on skilled labor and previously faced barriers to hiring such talent. To examine this,

[10] For the firm-level R&D measure, we categorize firms into high and low R&D expense groups only among those that reported R&D expenses, representing approximately 40% of our observations.

we partition firms into subsamples with high and low labor frictions and re-estimate Equation (1) conditional on various measures of labor market constraints.

As highlighted in FTC Chair Lina Khan's statement, depriving new businesses of access to skilled workers can stifle competition. For instance, in the highly concentrated glass manufacturing sector, incumbent firms were cited as having imposed non-compete agreements on thousands of employees—effectively locking in highly specialized talent and restricting rival firms' access to qualified labor.

Consistent with this reasoning, we expect that firms operating in Income Restrictions states, where the FTC's ban meaningfully expands skilled labor mobility, will benefit more if they are heavily dependent on such talent. Specifically, firms with greater exposure to skilled labor frictions should exhibit stronger positive stock return reactions to the policy change. Table 8 presents the results.

[Please Insert Table 8 Here]

Columns (1) and (2) compare the buy-and-hold returns (BHRs) for firms with high versus low skilled labor risk, as measured by Qiu and Wang (2021). We find that firms with greater exposure to skilled labor risk exhibit significantly more positive stock price reactions to the FTC's rule change (column (1)), while firms with low skilled labor risk show no such effect (column (2)). Similarly, columns (3) and (4) distinguish between firms that rely heavily on highly skilled labor and those that do not, following Belo et al. (2017). The effects are concentrated among firms with greater reliance on skilled labor. These results are intuitive: although firms with high skilled labor risk may worry about increased talent attrition following the ban, they are also better positioned to benefit from the expanded mobility of skilled professionals—particularly if they previously faced hiring frictions due to NCAs. The positive stock price response suggests that, on balance, the benefits from accessing a broader labor pool outweigh the potential costs of talent loss. In contrast, firms less reliant on skilled labor—such as those in retail or wholesale sectors—are less affected by changes in labor mobility regulations.

We next consider heterogeneity based on the enforceability of the Inevitable Disclosure Doctrine (IDD), which can limit skilled labor mobility even in the absence of NCAs (Klasa et al., 2018; Qiu and Wang, 2018). If firms operate in states where IDD is recognized, then the FTC's NCA ban may have limited impact on actual labor mobility. Indeed, comparing columns (5) and (6), we find that firms located in states where the IDD is not recognized experience stronger positive market reactions—consistent with the ban having greater bite where labor mobility restrictions are fully removed.

Furthermore, we construct a composite measure of firm labor exposure using the first principal component of *Labor Skill*, *Skilled Labor Risk*, and the *Non-IDD* indicator. We split the sample based on this composite index. Firms with high labor exposure exhibit significant positive reactions to the FTC's rule change (column (7)), whereas firms in the low labor exposure group do not (column (8)). These results reinforce the view that the benefits of increased labor mobility from the NCA ban accrue primarily to firms that are reliant on having access to skilled talent.

Lastly, we investigate how a firm's geographic dispersion in operations moderates the effects of the FTC's non-compete ban. Firms with limited geographic dispersion rely on a more restricted and concentrated labor pool, likely facing greater labor frictions. These firms may thus experience more pronounced effects from the FTC's ban on NCAs. We measure geographic dispersion by counting the number of unique states mentioned in each firm's 10-K filings (Garcia and Norli, 2012). Column (9) shows that the FTC's ban produces stronger positive stock price reactions for geographically concentrated firms, as it alleviates local labor frictions by expanding their access to skilled workers. In contrast, geographically dispersed firms, which draw from multiple state labor pools, show a reduced effect (column (10)), reflecting the varied state-level impacts of the FTC's ban. This contrast highlights how geographic concentration can amplify labor frictions that the FTC's policy helps to alleviate.

3.2.4 Industry Leaders

While the FTC's non-compete ban levels the playing field for smaller, financially constrained, and knowledge-intensive firms, its impact on entrenched industry leaders is likely less favorable. These larger, well-capitalized firms have historically maintained a competitive edge by restricting employee mobility, using non-compete agreements to prevent key talent from joining competitors or launching spinouts. By insulating themselves from talent-driven competition, industry leaders have reinforced their market dominance—not necessarily by outperforming rivals in innovation, but by limiting others' access to strategic human capital.

The removal of these legal restrictions erodes that structural advantage, granting financially weaker and innovation-focused challengers—who rely heavily on external skilled talent—greater opportunities to compete. In this way, the FTC's policy serves not only to enhance overall labor market efficiency, but to reallocate competitive advantage from firms that have used legal instruments to preserve dominance toward those that depend on attracting talent to drive innovation. As a result, while knowledge-intensive firms gain from the expanded mobility of skilled labor, industry leaders—who once benefited from labor frictions—may lose ground in an environment of heightened competition for human capital.

To examine this dynamic, Table 9 presents OLS regression results for 7-day buy-and-hold returns, incorporating interactions with industry leader indicators. Industry leaders are defined as the top 1% of firms with the highest market share in each industry prior to the FTC's non-compete ban, using both traditional two-digit SIC and text-based two-digit ETNIC (Embeddings-based TNIC) industry classifications. If an industry has fewer than 100 firms, the firm with the highest market share is designated as the industry leader. The first two columns of Table 9 identify industry leaders based on two-digit SIC industry classification, with and without control variables, while the last two columns apply the two-digit ETNIC classification, which follows the word2vec text-based industry classification developed by Hoberg and Phillips (2025). All regressions include the same set of control variables as in the baseline results presented in Table 3.

[Please Insert Table 9 Here]

The findings reveal a stark contrast between industry leaders and their smaller competitors. While the coefficient estimate on *Income Restrictions* remains significantly positive at the 1% level, the coefficient estimate on the interaction term *Income Restrictions* × *Top1pct Market Share SIC2* is significantly negative at the 1% level, with an economically large effect of approximately –4 percentage points. A similar pattern emerges when using the ETNIC industry classification, where the interaction term *Income Restrictions* × *Top1pct Market Share ETNIC2* is also significantly negative at the 1% level, with a comparable magnitude. These results highlight a critical implication: while smaller, younger, and financially constrained firms benefit from the FTC's non-compete ban, industry leaders appear to lose. The policy shift weakens their ability to retain key talent, eroding a structural advantage that previously reinforced their market dominance.

4. Further Tests

4.1 Labor Market Regulations

As a robustness check, we further control for state-level labor market regulatory conditions, including wrongful discharge laws (e.g., *Good Faith*, *Implied Contract*, and *Public Policy*) and the implementation of the Inevitable Disclosure Doctrine in each state (e.g., *IDD* and *IDD Robust*) (e.g., Autor, Donohue, and Schwab, 2004; Acharya, Baghai, and Subramanian, 2014; Serfling, 2016; Klasa et al., 2018; Qiu and Wang, 2018). The results are presented in Table A7 in the Online Appendix.

Panel A of Table A7 in the Online Appendix shows that our main finding—the strong positive stock price reactions of firms located in Income Restrictions states to the FTC's non-compete ban—remains qualitatively unchanged after the inclusion of additional controls for local labor market regulations. In panel A, we measure the Inevitable Disclosure Doctrine (*IDD*) based on the seminal work of Png and Samila (2013) and incorporates the IDD shocks identified by Qiu and Wang (2018), who expanded the list using a series of legal studies and a comprehensive review of IDD-related court cases (e.g., Qiu and Wang, 2018). To further demonstrate robustness, we conduct an additional test using the IDD measures proposed by Klasa et al. (2018) as an alternative control (*IDD Robust*) in panel B of Table A7. The results, presented in both panels A and B, align with the baseline regressions even with the inclusion of these additional controls.

4.2 Local Economic Conditions

We also include state-level economic variables—per capita income (*Per Capita State Income*), total income (*Total State Income*), and income growth (*State Income Growth*)—to capture the development level, size, and growth dynamics of the local economy, as these factors may influence intellectual property protections and labor mobility at the state level (e.g., Qiu and Wang, 2018). Data for these variables are obtained from the U.S. Bureau of Economic Analysis.[11] Results in Table A8 in the Online Appendix show that the main findings remain qualitatively robust when controlling for local economic conditions. Specifically, the coefficient estimates of *Income*

[11] We use the data for the 4th Quarter of 2023.

Restrictions are consistently positive and statistically significant at the 1% level across all regressions.

4.3 Alternative Clustering Methods

To further address potential correlations in stock return standard errors, we re-estimate Equation (1) using alternative clustering methods. First, as the FTC's non-compete ban may similarly impact firms within the same industry, we cluster standard errors at the industry level to account for potential correlations among stock returns within industries. Online Appendix Table A9 presents these results: Columns (1) and (4) show regression results for 7-day BHRs and CARs with industry-level clustering, while Columns (2) and (5) cluster standard errors at both the state and industry levels. The coefficient estimates for *Income Restrictions* remain positive and significant at the 1% level across all specifications. Additionally, the literature notes limitations in clustering with few clusters (e.g., Bertrand, Duflo, and Mullainathan, 2004; Hansen, 2007). Although this is not a concern in our study (given the varied effects of the FTC's ban across states and industries), we also calculate bootstrapped standard errors as a robustness check.[12] Columns (3) and (6) confirm that our results remain qualitatively consistent with bootstrapped standard errors.

4.4 Excluding California Firms

Moreover, as the reference group (i.e., firms in the Full Ban states) includes California firms, many of which are predominantly tech companies, we conduct a robustness test excluding all California firms. Table A10 in the Online Appendix shows that the FTC's non-compete ban continues to result in positive stock price reactions in all regressions after removing California firms. The coefficient estimates for *Income Restrictions* remain positive across all specifications and are significant at least at the 5% level. These results are qualitatively similar to the baseline results.

[12] We calculate the standard errors by bootstrapping 1,000 samples from our regression sample and estimating the regression coefficient estimates 1,000 times.

4.5 Expanded Firm Sample

In Table A11 in the Online Appendix, we further present OLS regression results for 7-day buy-and-hold returns and cumulative abnormal returns around the FTC's non-compete ban announcement, using a broad public firm sample that does not control for firm-level variables and is therefore not constrained by their data availability. This expanded sample includes 4,620 public firms with available stock return data from CRSP. The findings remain qualitatively similar to those from our main sample. The FTC's NCA ban led to an increase of approximately 0.3 to 1.4 percentage points in firms' stock returns over the 7-day event window, with the strongest reactions observed in states where NCAs were previously enforceable for higher-income employees (the Income Restrictions states).

4.6 Alternative Measures of State-level Non-compete Enforcement

In our main analyses, we classify all states into four categories—Full Ban, Income Restrictions, Other Restrictions, and Court Discretion—based on their pre-FTC ban regulation of non-compete agreements at the end of March 2024, following the Economic Innovation Group's state non-compete law tracker. This classification captures key differences in state-level NCA policies, such as restrictions that allow non-competes only for employees earning above a specified income threshold. To test the robustness of our findings, Table A12 presents OLS regression results using an alternative measure of state-level non-compete enforcement: the covenants-not-to-compete enforcement index (NC Index) from Garmaise (2011), Ertimur, Rawson, Rogers, and Zechman (2018), and Bai, Eldemire, and Serfling (2024), with higher index values reflecting greater enforceability of CNCs by state courts.

Specifically, we replace our primary categorical indicators with three NC Index-based measures that quantify the degree of NCA enforceability across states. Column (1) introduces the indicator variable *NC Index Above Zero*, which equals one if the NC Index exceeds zero, capturing states where NCAs had any level of enforceability. Column (2) raises the threshold to *NC Index Above One*, while Column (3) applies *NC Index Above Two* to reflect greater non-compete enforceability. Across all specifications, the coefficient estimates of these indicators remain significantly positive, with magnitudes ranging from 0.39 to 0.47 percentage points, again suggesting that firms in states with enforceable NCAs, on average, experienced positive stock return reactions to the FTC's NCA ban.

5. Conclusion

In today's knowledge-based economy—characterized by rapid innovation, widespread AI applications, and shorter innovation cycles—skilled talent has become a critical asset. Non-compete agreements (NCAs), while historically used to retain key employees, may hinder the mobility and collaboration necessary for technological progress. The FTC's recent nationwide ban on NCAs aims to foster a more dynamic labor market by enabling firms to access and retain the skilled talent essential for innovation and growth.

In this study, we examine stock price reactions to the FTC's ban across firms with varying characteristics and regulatory exposure. We find that, on average, firms headquartered in states that previously enforced NCAs for higher-income skilled employees experienced significantly positive abnormal stock returns. This suggests that investors anticipate productivity gains from enhanced labor mobility. The effect is particularly pronounced among firms with substantial financial constraints, higher stock return volatility, greater knowledge intensity and stronger dependence on skilled labor—traits often associated with younger, innovation-driven challengers. In contrast, industry leaders—defined as firms with the highest market share in their respective industries—exhibit significantly negative returns, indicating an erosion of competitive advantage previously afforded by NCAs. These results align with the view that NCAs disproportionately restricted access to talent among resource-constrained firms (Jeffers, 2024), and that the FTC's ban levels the playing field by enabling broader access to specialized labor.

This study contributes to the literature on labor market regulation, corporate strategy, and competitive dynamics by illuminating how regulatory changes targeting NCAs affect firm value. The findings have implications for policymakers, managers, and investors, emphasizing the broader economic value of skilled labor mobility. In an era increasingly defined by AI-driven innovation, the ability to attract and deploy talent rapidly and flexibly is vital. Our results underscore how dismantling legal frictions in labor markets can empower challenger firms and support a more inclusive and dynamic innovation ecosystem.

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Figure 1
Enforcement Status of Non-competes Across States in the U.S. Before the FTC's Ban

Figure 1 maps the enforcement status of non-competes across various states in the U.S. at the end of March 2024 prior to the FTC's nationwide NCAs ban based on the Economic Innovation Group's state non-competes law tracker (see https://eig.org/state-noncompete-map/). We categorize states into four broad groups: Full Ban, Income Restrictions, Other Restrictions, and Court Discretion, each represented by a different shade of green.

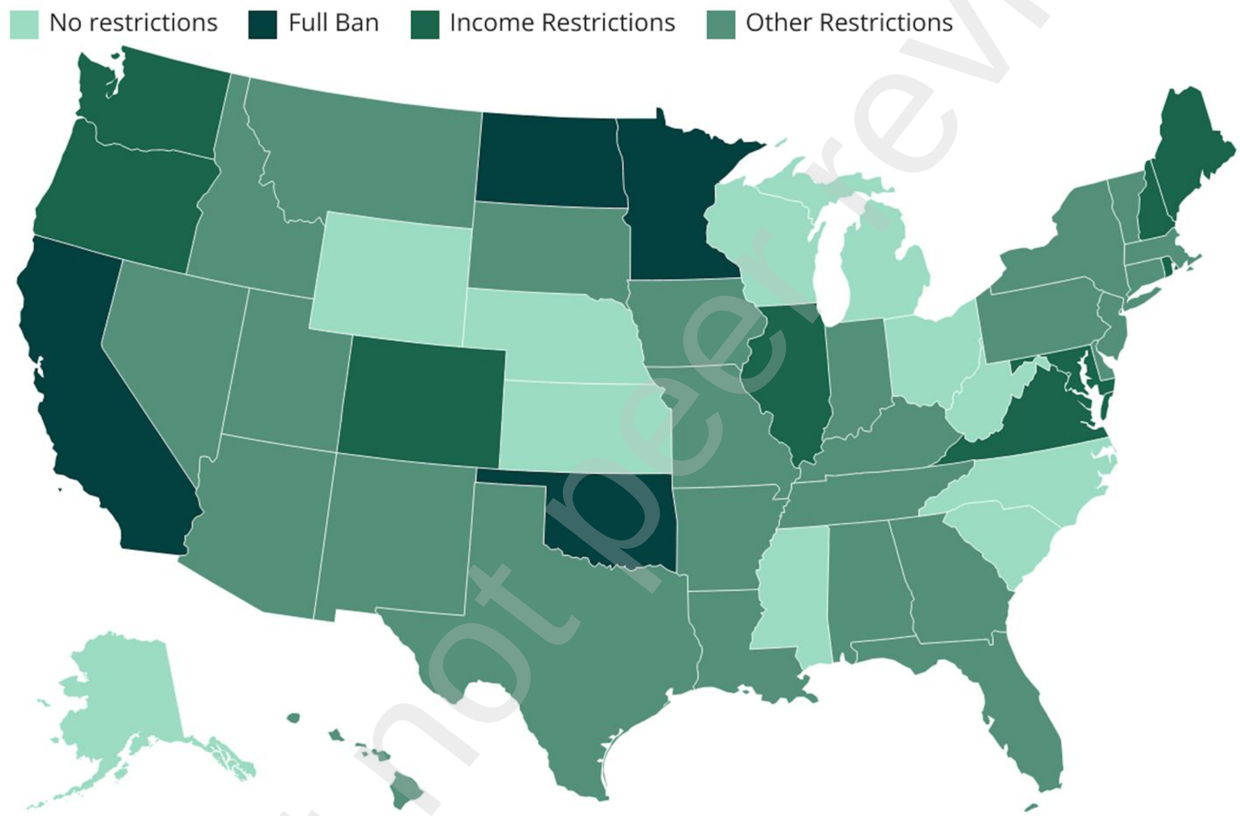

Figure 2
Buy-and-Hold Returns and Enforcement Status of Non-competes around the FTC's Non-compete Ban Announcement

Figure 2 shows the buy-and-hold stock returns (BHRs) for firms located in various states over the 7-day event window surrounding the FTC's non-compete ban. We sort states into four broad categories, including Full Ban, Income Restrictions, Other Restrictions, and Court Discretion, according to the enforcement status of non-competes across various states in the U.S. prior to the FTC's ban. We use Full Ban state average BHRs as the reference group, and then plot the other three types of states' BHRs above the reference group during the 7-day event window.

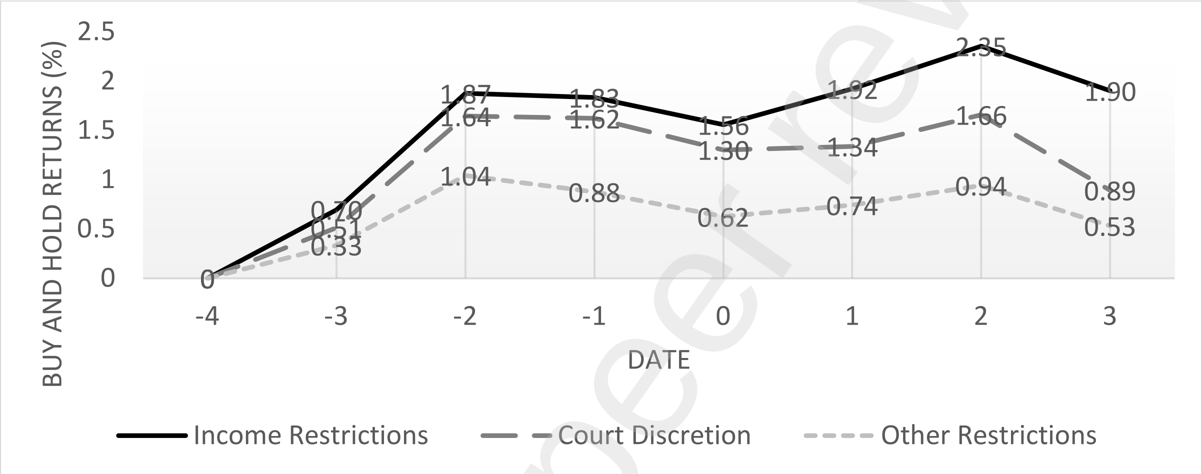

Figure 3
Frequency Histograms and Probability Density Function of Regression Coefficient Estimates for Income Restrictions from 1,000 Bootstrapped Samples

Figure 3 plots the frequency histograms and probability density function of the regression coefficient estimates for the *Income Restrictions* indicator, derived from 1,000 bootstrapped pseudo samples. The vertical dotted line in the middle represents the mean (0.006) of these bootstrapped pseudo coefficient estimates, while the vertical solid line on the right marks the actual coefficient estimate (1.268).

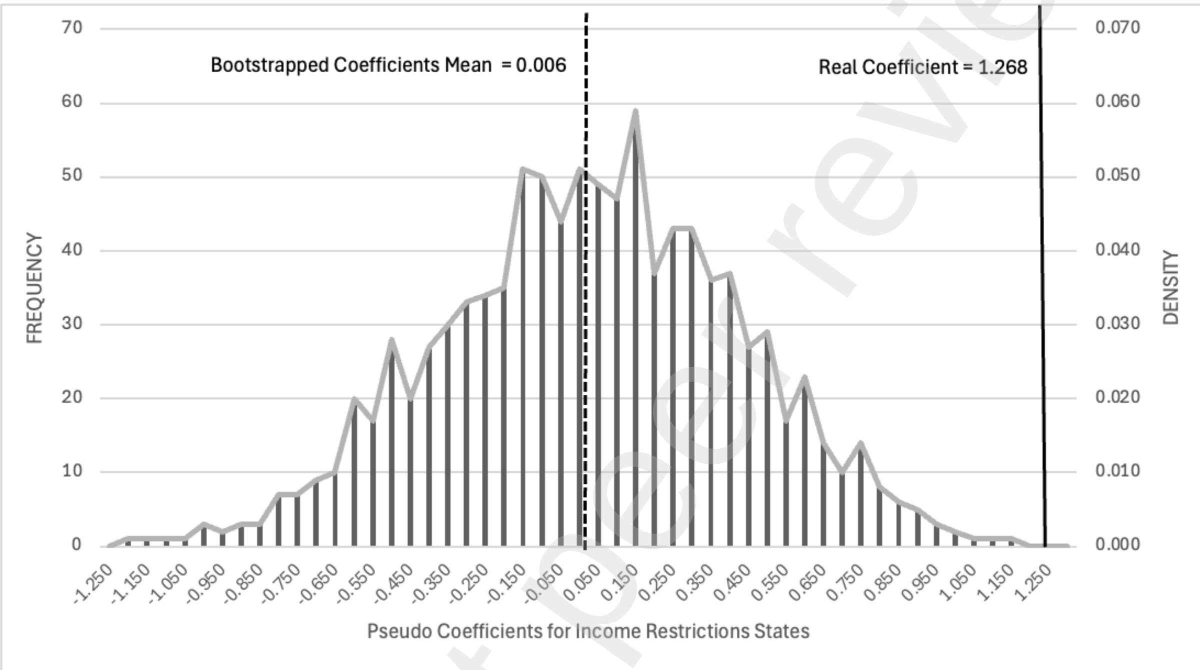

Table 1
Current Status of Non-compete Agreement Enforcement by State before the FTC's Non-Compete Ban

This table summarizes the most recent updated statutory restrictions placed on non-competes in each state at the end of March 2024 before the FTC's nationwide ban on non-competes. We sort states into four broad categories according to the Economic Innovation Group's State Non-Compete Law Tracker (see https://eig.org/state-noncompete-map/). Full Ban states completely prohibit the use of non-compete agreements in employment contexts. Income Restriction states set an income threshold to determine which employees may be subject to non-compete agreements. Other Restrictions states impose other (non-income-related) limitations on non-compete agreements, such as restrictions on their duration or the industries where they apply. Court Discretion states lack specific legislation governing the circumstances under which non-compete agreements are restricted; whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts. Detailed explanations of the statute for each state before the shock are provided in Online Appendix Table A2.

State Name	Full Ban	Income Restrictions	Other Restrictions	Court Discretion
Alabama			√	
Alaska				√
Arizona			√	
Arkansas			√	
California	√			
Colorado		√		
Connecticut			√	
Delaware			√	
District of Columbia		√		
Florida			√	
Georgia			√	
Hawaii			√	
Idaho			√	
Illinois		√		
Indiana			√	
Iowa			√	
Kansas				√
Kentucky			√	
Louisiana			√	
Maine		√		
Maryland		√		
Massachusetts			√	
Michigan				√
Minnesota	√			
Mississippi				√
Missouri			√	

Montana			√	
Nebraska				√
Nevada			√	
New Hampshire		√		
New Jersey			√	
New Mexico			√	
New York			√	
North Carolina				√
North Dakota	√			
Ohio				√
Oklahoma	√			
Oregon		√		
Pennsylvania				√
Rhode Island		√		
South Carolina				√
South Dakota			√	
Tennessee			√	
Texas			√	
Utah			√	
Vermont			√	
Virginia		√		
Washington		√		
West Virginia				√
Wisconsin				√
Wyoming				√

Table 2
Summary Statistics

This table reports sample descriptive statistics. The sample consists of 2,839 firm observations with no missing CRSP-Compustat data that covers the period from January 1, 2023 to April 30, 2024. A detailed description of the variables is presented in Online Appendix Table A1. All dollar values are in 2023 constant dollars. All continuous variables are winsorized at the 1st and 99th percentiles. We report the means, medians, standard deviations, 25th and 75th percentiles, and numbers of observations for variables.

Variables	No. of Obs.	Mean	Median	Std. Dev.	P25	P75
Buy-and-Hold Return (-3, +3)	2839	1.625	1.952	6.901	-1.550	5.079
Buy-and-Hold Return (-2, +2)	2839	0.972	1.425	5.862	-1.484	3.924
Cumulative Abnormal Return (-3, +3)	2839	0.135	0.500	6.859	-2.829	3.572
Cumulative Abnormal Return (-2, +2)	2839	0.268	0.783	5.865	-2.113	3.233
Size	2839	7.009	7.218	2.387	5.477	8.670
Leverage	2839	25.147	19.045	22.960	5.107	39.210
MTB	2839	4.161	2.005	7.149	1.082	4.063
Roa	2839	-3.896	0.162	11.309	-4.452	1.330
Past Return	2839	11.036	3.943	57.434	-19.429	31.624
Vol	2839	42.355	33.665	27.434	23.760	52.550
Illiquidity	2839	9.108	0.411	22.451	0.047	17.767
KZ	2446	-18.833	-2.305	73.631	-11.879	0.739
WW	2490	-10.203	-0.359	37.903	-3.082	-0.200
HP	2839	-4.007	-4.099	0.951	-5.001	-3.308
Z-Score	2239	-1.978	0.564	8.933	-2.165	1.707
Dividend	2839	0.452	0.000	0.498	0.000	1.000
Text-based Equity Constraint	1779	0.026	0.051	0.473	-0.338	0.367
Text-based Debt Constraint	1779	0.111	-0.067	0.683	-0.373	0.436
Roa Vol	2839	15.223	4.517	41.297	1.706	12.769
Cash Flow Vol	2839	17.874	5.410	45.383	2.014	12.286
Ivol	2839	6.844	5.053	6.194	3.403	8.680
Labor Skill	2509	0.391	0.355	0.177	0.285	0.523
IDD	2839	0.251	0.000	0.434	0.000	1.000
Labor Skill Risk	1660	4.961	4.000	3.920	2.000	7.000
Labor Exposure	1434	-0.000	-0.076	1.110	-0.790	0.776
SG&A	2839	91.348	20.524	439.544	3.630	42.073
R&D	2839	209.343	0.000	1196.869	0.000	9.271
Geographic Dispersion	2839	7.426	6.000	6.689	4.000	9.000
Hightech	2839	0.386	0.000	0.487	0.000	1.000
Good Faith	2839	0.396	0.000	0.489	0.000	1.000
Implied Contract	2839	0.814	1.000	0.389	1.000	1.000
Public Policy	2839	0.888	1.000	0.315	1.000	1.000

IDD Robust	2839	0.399	0.000	0.490	0.000	1.000
Per Capita State Income	2839	11.196	11.195	0.133	11.101	11.308
Total State Income	2839	13.722	13.545	0.952	13.061	14.525
State Income Growth	2839	1.017	1.008	0.216	0.829	1.186

Table 3
Firms' Buy-and-Hold Stock Returns around FTC's Non-Compete Ban

This table reports the OLS regression results for 7-day buy-and-hold returns. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions, and Court Discretion) according to the most recent updated statutory restrictions placed on non-competes in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)	(4) Buy-and-Hold Return (-3, +3)
Income Restrictions	1.906***	1.177***	1.493***	1.268***
	(0.166)	(0.225)	(0.228)	(0.249)
Other Restrictions	0.535	0.116	0.281	0.171
	(0.390)	(0.232)	(0.306)	(0.214)
Court Discretion	0.899	0.323	0.303	0.259
	(0.544)	(0.455)	(0.526)	(0.469)
Size			0.131*	0.079
			(0.075)	(0.081)
Leverage			0.019***	0.002
			(0.006)	(0.005)
MTB			-0.019	-0.015
			(0.022)	(0.024)
Roa			0.063***	0.040**
			(0.017)	(0.018)
Past Return			0.010***	0.008**
			(0.003)	(0.003)
Vol			-0.010	0.001
			(0.008)	(0.008)
Illiquidity			-0.016**	-0.019**
			(0.008)	(0.008)
Industry FE	No	Yes	No	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.008	0.097	0.062	0.114

Table 4
Regression Coefficient Estimates from 1,000 Bootstrapped Pseudo Samples

This table reports the summary statistics of the regression coefficient estimates generated using 1,000 bootstrapped pseudo samples. We randomly reassign each sample firm's headquarters state statutory restriction on non-competes—prior to the FTC's nationwide ban—to one of four categories (including Full Ban, Income Restrictions, Other Restrictions, or Court Discretion) based on their actual sample probability distribution. This process is repeated 1,000 times to generate 1,000 pseudo samples, which we then use to reestimate the regression specification from Table 3, column (4). The table presents the summary statistics for the regression coefficient estimates derived from these 1,000 bootstrapped samples, reporting the mean, standard deviation, *t*-values, minimum, maximum, and percentile distributions. For comparison, we also report the coefficient estimates, standard errors, and *t*-values derived from our actual regression sample. In all OLS regressions, the dependent variable is 7-day buy-and-hold returns of 2,839 firm observations from April 18, 2024 to April 26, 2024. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

	Actual Sample			Bootstrapped Pseudo Samples											
	Coeff	S.D.	*t*-value	Mean	S.D.	*t*-value	Min	P5	P10	P25	P50	P75	P90	P95	Max
Income Restrictions	1.268***	0.249	5.092	0.006	0.396	0.015	-1.217	-0.647	-0.529	-0.255	0.017	0.280	0.520	0.652	1.134
Other Restrictions	0.171	0.214	0.799	0.025	0.311	0.080	-0.910	-0.498	-0.371	-0.198	0.034	0.231	0.426	0.536	0.920
Court Discretion	0.259	0.469	0.552	0.007	0.446	0.016	-1.175	-0.713	-0.562	-0.315	0.010	0.309	0.575	0.731	1.396

Table 5
Firm Financial Constraints and the Stock Price Reactions to the FTC's Non-Compete Ban

This table reports the OLS regression results for 7-day buy-and-hold returns conditional on different measures of financial constraints. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into high- and low-groups based on their different measures of financial constraints before the FTC's nationwide non-competes rule banning shock. The Chi2 and the *p*-values of Chow tests for coefficient differences among income restrictions firms are also presented below. Regressions include the same set of controls that appeared in the baseline results (i.e., Table 3). Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Variables	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)	Buy-and-Hold Return (-3, +3)
Financial Constraint Measures	High KZ	Low KZ	High WW	Low WW	High HP	Low HP	High Z-Score	Low Z-Score	With Dividend	Without Dividend	High LW Equity Constraint	Low LW Equity Constraint	High LW Debt Constraint	Low LW Debt Constraint
Income Restrictions	1.867***	0.789**	1.880***	0.515	1.594***	0.948**	0.298	2.927***	0.478	1.914***	1.852***	0.515	1.258**	0.928*
	(0.466)	(0.376)	(0.548)	(0.404)	(0.465)	(0.415)	(0.243)	(0.487)	(0.336)	(0.283)	(0.664)	(0.540)	(0.596)	(0.510)
Other Restrictions	0.203	0.383	-0.275	0.497**	0.126	0.255	0.089	-0.114	0.193	0.088	0.886*	-0.310	-0.614	1.073***
	(0.366)	(0.257)	(0.362)	(0.236)	(0.311)	(0.236)	(0.301)	(0.430)	(0.147)	(0.313)	(0.464)	(0.396)	(0.384)	(0.366)
Court Discretion	1.045*	-0.089	-0.460	1.044***	-0.987	1.009**	0.190	-1.077	0.851***	-0.614	-0.529	0.152	-0.061	-0.423
	(0.579)	(0.600)	(0.553)	(0.382)	(0.790)	(0.417)	(0.425)	(1.005)	(0.237)	(1.054)	(1.448)	(0.375)	(0.394)	(1.283)
Chow Test Chi2 for Income Restrictions	5.870		4.370		0.840		18.030		8.860		2.430		0.370	
Chow Test *P*-Value for Income Restrictions	0.015		0.037		0.359		0.000		0.003		0.119		0.543	

Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	1,221	1,212	1,235	1,240	1,415	1,419	1,115	1,106	1,277	1,551	875	885	884	873
Adj R2	0.127	0.174	0.110	0.149	0.120	0.121	0.113	0.130	0.139	0.123	0.140	0.108	0.128	0.120

Table 6
Firm Risks and the Stock Price Reactions to the FTC's Non-Compete Ban

This table reports the OLS regression results for 7-day buy-and-hold returns conditional on different measures of firm risks. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into high- and low-groups based on their different measures of firm volatilities before the FTC's nationwide non-competes rule banning shock. The Chi2 and the *p*-values of Chow tests for coefficient differences among income restrictions firms are also presented below. Regressions include the same set of controls that appeared in the baseline results (i.e., Table 3). Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)	(4) Buy-and-Hold Return (-3, +3)	(5) Buy-and-Hold Return (-3, +3)	(6) Buy-and-Hold Return (-3, +3)	(7) Buy-and-Hold Return (-3, +3)	(8) Buy-and-Hold Return (-3, +3)
Firm Volatilities Measures	High Vol	Low Vol	High Roa Vol	Low Roa Vol	High Cash Flow Vol	Low Cash Flow Vol	High Ivol	Low Ivol
Income Restrictions	2.749***	0.112	2.645***	-0.318	2.049***	0.629	2.554***	0.285
	(0.413)	(0.194)	(0.528)	(0.390)	(0.529)	(0.406)	(0.491)	(0.260)
Other Restrictions	0.264	0.013	0.275	-0.318	0.571	-0.099	-0.014	0.157
	(0.251)	(0.236)	(0.376)	(0.230)	(0.546)	(0.274)	(0.355)	(0.209)
Court Discretion	0.354	-0.070	-0.377	0.184	-0.755	0.384	-0.790	0.606**
	(1.101)	(0.274)	(0.984)	(0.317)	(0.811)	(0.402)	(1.014)	(0.239)
Chow Test Chi2 for Income Restrictions	28.830		14.400		2.380		9.420	
Chow Test *P*-Value for Income Restrictions	0.000		0.000		0.123		0.002	
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	1,416	1,417	1,418	1,416	1,415	1,416	1,413	1,414
Adj R2	0.140	0.119	0.121	0.108	0.138	0.099	0.123	0.134

Table 7
Firm Knowledge Intensity and the Stock Price Reactions to the FTC's Non-Compete Ban

This table reports the OLS regression results for 7-day buy-and-hold returns conditional on different measures of firm knowledge intensity. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into high- and low-groups based on their different measures of knowledge intensity before the FTC's nationwide non-competes rule banning shock. The Chi2 and the *p*-values of Chow tests for coefficient differences among income restrictions firms are also presented below. Regressions include the same set of controls that appeared in the baseline results (i.e., Table 3). Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)	(4) Buy-and-Hold Return (-3, +3)	(5) Buy-and-Hold Return (-3, +3)	(6) Buy-and-Hold Return (-3, +3)	(7) Buy-and-Hold Return (-3, +3)	(8) Buy-and-Hold Return (-3, +3)	(9) Buy-and-Hold Return (-3, +3)	(10) Buy-and-Hold Return (-3, +3)
Knowledge Intensity Measures	High SG&A	Low SG&A	High R&D	Low R&D	High Industry SG&A	Low Industry SG&A	High Industry R&D	Low Industry R&D	Hightech	Non Hightech
Income Restrictions	1.829***	0.588	0.942	0.555	1.976***	0.583	1.930***	0.606*	2.161***	0.714**
	(0.359)	(0.437)	(0.606)	(0.534)	(0.318)	(0.389)	(0.323)	(0.346)	(0.581)	(0.353)
Other Restrictions	0.066	0.258	-0.040	0.089	0.255	0.044	0.448	-0.112	0.525*	-0.143
	(0.343)	(0.392)	(0.406)	(0.510)	(0.347)	(0.277)	(0.310)	(0.225)	(0.291)	(0.247)
Court Discretion	0.641**	-0.136	-0.088	-0.337	-0.139	0.353	0.003	0.355	-0.804	0.500
	(0.312)	(0.727)	(1.061)	(0.540)	(0.982)	(0.412)	(0.997)	(0.386)	(0.927)	(0.307)
Chow Test Chi2 for Income Restrictions	3.880		0.030		5.000		9.350		3.300	
Chow Test *P*-Value for Income Restrictions	0.049		0.871		0.025		0.002		0.069	

Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	1,414	1,411	593	595	1,422	1,414	1,420	1,418	1,097	1,742
Adj R2	0.132	0.137	0.118	0.085	0.115	0.105	0.117	0.094	0.099	0.090

Table 8
Labor Frictions and the Stock Price Reactions to the FTC's Non-Compete Ban

This table reports the OLS regression results for 7-day buy-and-hold returns conditional on different measures of labor frictions. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into high- and low-groups based on their different measures of labor frictions before the FTC's nationwide non-competes rule banning shock. The Chi2 and the *p*-values of Chow tests for coefficient differences among income restrictions firms are also presented below. Regressions include the same set of controls that appeared in the baseline results (i.e., Table 3). Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)	(4) Buy-and-Hold Return (-3, +3)	(5) Buy-and-Hold Return (-3, +3)	(6) Buy-and-Hold Return (-3, +3)	(7) Buy-and-Hold Return (-3, +3)	(8) Buy-and-Hold Return (-3, +3)	(9) Buy-and-Hold Return (-3, +3)	(10) Buy-and-Hold Return (-3, +3)
Labor Market Measures	High Skilled Labor Risk	Low Skilled Labor Risk	High Labor Skill	Low Labor Skill	Non-IDD States	IDD States	High Labor Exposure	Low Labor Exposure	Low Geographic Dispersion	High Geographic Dispersion
Income Restrictions	2.019***	-0.215	1.726***	0.929*	1.410***	0.902**	1.791**	0.704	1.486**	0.845
	(0.530)	(0.401)	(0.402)	(0.551)	(0.356)	(0.371)	(0.810)	(0.707)	(0.655)	(0.508)
Other Restrictions	0.076	-0.116	0.292	0.121	0.165	0.021	0.438	-0.466	0.244	-0.016
	(0.350)	(0.312)	(0.242)	(0.477)	(0.254)	(0.403)	(0.363)	(0.503)	(0.381)	(0.285)
Court Discretion	0.269	0.026	0.634	-0.106	0.824*	-0.658	0.634	0.256	0.013	0.338
	(0.311)	(0.544)	(0.730)	(0.475)	(0.466)	(0.487)	(0.795)	(0.516)	(0.769)	(0.331)
Chow Test Chi2 for Income Restrictions	10.320		0.870		0.310		1.120		0.220	
Chow Test *P*-Value for Income Restrictions	0.001		0.350		0.580		0.291		0.640	

Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	958	688	1,662	839	2,128	705	708	715	1,370	1,455
Adj R2	0.172	0.159	0.140	0.083	0.132	0.124	0.182	0.137	0.154	0.100

Table 9
Industry Leaders and the Stock Price Reactions to the FTC's Non-Compete Ban

This table reports the OLS regression results for 7-day buy-and-hold returns, further interacting with different industry leaders' indicators. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. Industry leaders are defined as the top 1% of firms that owned most of the market share in each industry (i.e. two-digit SIC or two-digit ETNIC) before the FTC's nationwide ban on non-competes. If the number of firms in an industry is less than one hundred, we select the firm that has the highest market share as the industry leader in each industry. Columns (1) and (2) identify industry leaders according to the two-digit SIC industry classification with and without control variables. Columns (3) and (4) identify industry leaders according to the two-digit ETNIC industry classification with and without control variables. The two-digit ETNIC industries are the word2vec text-based industry classification obtained from Hoberg and Phillps (2025). Regressions include the same set of controls that appeared in the baseline results (i.e., Table 3). Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)	(4) Buy-and-Hold Return (-3, +3)
Income Restrictions*Top1pct Market Share SIC2	-3.922**	-3.897**		
	(1.527)	(1.640)		
Other Restrictions*Top1pct Market Share SIC2	0.891	1.337		
	(1.034)	(1.183)		
Court Discretion*Top1pct Market Share SIC2	1.040	1.319		
	(1.225)	(1.082)		
Top1pct Market Share SIC2	0.668	-0.552		
	(1.044)	(1.307)		
Income Restrictions *Top1pct Market Share ETNIC2			-3.711***	-4.186***
			(1.323)	(1.287)
Other Restrictions *Top1pct Market Share ETNIC2			0.615	1.200
			(1.086)	(1.086)
Court Discretion*Top1pct Market Share ETNIC2			-3.794*	-3.329
			(2.176)	(2.072)
Top1pct Market Share ETNIC2			0.334	-0.442
			(1.093)	(1.143)
Income Restrictions	1.195***	1.289***	1.190***	1.278***
	(0.228)	(0.251)	(0.228)	(0.253)
Other Restrictions	0.092	0.141	0.083	0.105
	(0.248)	(0.233)	(0.243)	(0.216)
Court Discretion	0.303	0.240	0.461	0.371

	(0.469)	(0.489)	(0.407)	(0.430)
Size		0.091		0.087
		(0.087)		(0.081)
Leverage		0.002		0.003
		(0.005)		(0.005)
MTB		-0.014		-0.015
		(0.024)		(0.024)
Roa		0.040**		0.040**
		(0.018)		(0.018)
Past Return		0.008**		0.008**
		(0.003)		(0.003)
Vol		0.001		0.001
		(0.008)		(0.008)
Illiquidity		-0.019**		-0.019**
		(0.008)		(0.008)
Industry FE	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.097	0.115	0.098	0.116

Online Appendix

Table A1
Variables Definitions

Variables	Descriptions	Source
Buy-and-Hold Return	Individual daily compounding returns of all common stocks (CRSP share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. We calculate both the 7-day (from -3 to +3) and 5-day (from -2 to +2) buy-and-hold returns.	CRSP
Cumulative Abnormal Return	Cumulative abnormal returns estimated using the market-adjusted model. We use the S&P 500 stock market index as the market portfolio. The market-adjusted model calculates daily abnormal stock returns by directly subtracting the actual market returns from the individual stock returns. We calculate both the 7-day (from -3 to +3) and 5-day (from -2 to +2) cumulative abnormal returns.	CRSP
Size	The natural logarithm of total assets measured in $ millions.	Compustat
Roa	Income before extraordinary items scaled by total assets.	Compustat
MTB	Market value of equity divided by book value of equity.	Compustat
Leverage	The total of long-term debt and debt in current liabilities divided by total assets.	Compustat
Past Return	Past stock return for the last fiscal year in percentage points.	CRSP
Vol	Annualized daily stock return volatility in each month (we require at least 17 non-missing daily returns in a month for the calculation), averaged over the last fiscal year.	CRSP
Illiquidity	Following Amihud (2002), illiquidity is measured as the average daily ratio of absolute return to the dollar volume of each stock in percentage for the last fiscal year. Stocks admitted in the last fiscal year have more than 200 days of data for the calculation of the characteristics and their end-of-year price exceeds $5.	Compustat
Roa Vol	Standard deviation of the past five years' returns on assets in percentage points. We require at least three years' numbers to calculate the volatility.	Compustat
Cash Flow Vol	Standard deviation of the past five years' cash flow from operations excluding extraordinary items scaled by the beginning total assets in percentage points. We require at least three years' numbers to calculate the volatility.	Compustat
Ivol	Annualized standard deviation of the residuals from regressing daily individual stock returns on the Fama-French three-factors in each month (we require at least 17 non-missing daily returns in a month for the regression), averaged over the last fiscal year.	CRSP
KZ	As –1.001909[(IB + DP)/lagged PPENT] + 0.2826389[(AT + PRCC_F × CSHO - CEQ - TXDB)/AT] + 3.139193[(DLTT + DLC)/(DLTT + DLC + SEQ)] – 39.3678[(DVC + DVP)/lagged PPENT] – 1.314759[CHE/lagged PPENT].	Compustat
WW	As –0.091 [(IB + DP)/AT] – 0.062[indicator set to one if DVC + DVP is positive, and zero otherwise] + 0.021[DLTT/AT] – 0.044[log(AT)] + 0.102[average industry sales growth, estimated separately for each three-digit SIC industry and each year, with sales growth defined as above] – 0.035[sales growth].	Compustat
HP	As –0.737Size + 0.043Size2 – 0.040Age, where Size equals the log of inflation-adjusted Compustat item AT (in 2019 dollars), and Age is the number of years the firm is listed with a non-missing stock price on Compustat. In calculating the index, we cap Size at (the log of) $5.6 billion and Age at 50 years.	Compustat
Z-Score	As (1.2*WCAP + 1.4*RE + 3.3*PI + 0.999*SALE)/AT.	Compustat
Dividend	Takes value of 1 if a firm pays dividends at the end of the last fiscal year, and 0 otherwise.	Compustat
LW Equity Constraint	Equity constraint measures of Linn and Weagley (2024) are machine-learning extensions of the text-based financial constraint measures developed in Hoberg and Maksimovic (2015), which identify direct statements indicating financial constraints. Linn and Weagley (2024) adopt a machine learning algorithm, random forests, to estimate a multi-dimensional mapping between firm-level accounting variables and financial constraints. We use their equity-focused constraint measures estimated with the "Exogenous" model, which is cleaner compared with the full model.	Linn and Weagley (2023)

LW Debt Constraint	Debt constraint measures of Linn and Weagley (2024) are machine-learning extensions of the text-based financial constraint measures developed in Hoberg and Maksimovic (2015), which identify direct statements indicating financial constraints. Linn and Weagley (2024) adopt a machine learning algorithm, random forests, to estimate a multi-dimensional mapping between firm-level accounting variables and financial constraints. We use their Debt-focused constraint measures estimated with the "Exogenous" model, which is cleaner compared with the full model.	Linn and Weagley (2023)
Labor Skill	Following Belo et al. (2017), skill of an industry is defined as the percentage of workers that work on occupations that require a high level of training and preparation (i.e., occupations with Specific Vocational Preparation (SVP)>=7). Industry is defined by their four-digit NAICS codes after 2001. The SVP data is from the Dictionary of Occupational Titles: Revisited Fourth Edition, 1991 from the Department of Labor. They are obtained from the Inter-university Consortium for Political and Social Research (ICPSR) (study no. 6100 (v.1); DOI:10.3886). The data on the distribution of workers by occupation within an industry are from the Bureau of Labor Statistics (BLS), Occupational Employment Statistics (OES) program.	Belo et al. (2017)
Skilled Labor Risk	The risk of failing to attract and/or retain skilled labor. To quantify firms' skilled labor risk, Qiu and Wang (2021) develop a measure based on firms' discussions on risk related to skilled labor in their 10-K filings in the Securities and Exchange Commission's (SEC's) EDGAR database. Skilled labor risk as the total number of sentences including the keywords related to skilled labor risk in all three 10-K items.	Qiu and Wang (2021)
Labor Exposure	Using the PCA to extract the 1st principal component based on Labor Skill, Skilled Labor Risk and Non-IDD measures. We standardize the first two measures before running the PCA.	Belo et al. (2017), Qiu and Wang (2018) and Qiu and Wang (2021)
SG&A	Firms' SG&A spending scaled by total sales in percentage points.	Compustat
R&D	Firms' R&D spending scaled by total sales in percentage points.	Compustat
Industry SG&A	Average SG&A spending scaled by total sales for firms in the same first 3-digit SIC code industry in percentage points.	Compustat
Industry R&D	Average R&D spending scaled by total sales for firms in the same first 3-digit SIC code industry in percentage points.	Compustat
Geographic Dispersion	Garcia and Norli's (2012) measure of the firm's geographic dispersion based on the number of U.S. states mentioned in the firm's annual 10-K report.	Diego Garcia's Website
Hightech	An indicator equals to one if firms belong to any high-tech industries and zero otherwise. High-tech industries are defined based on the Fama-French 10-industry classification.	Kenneth French's Website
Good Faith	Binary variable that equals 1 if the state in which a firm is headquartered has adopted the good faith exception by year *t* and 0 otherwise.	Serfling (2016)
Implied Contract	Binary variable that equals 1 if the state in which a firm is headquartered has adopted the implied contract exception by year *t* and 0 otherwise.	Serfling (2016)
Public Policy	Binary variable that equals 1 if the state in which a firm is headquartered has adopted the public policy exception by year *t* and 0 otherwise.	Serfling (2016)
IDD	An indicator variable equals one if the states recognize the Inevitable Disclosure Doctrine (IDD), and zero otherwise.	Qiu and Wang (2018)
IDD Robust	An indicator variable equals one if the states recognize the Inevitable Disclosure Doctrine (IDD), and zero otherwise.	Klasa et al. (2018)
Per Capita State Income	Natural logarithm of per capita income of the state where firms' headquarters is located in.	Bureau of Economic Analysis

Total State Income	Natural logarithm of total income of the state where firms' headquarters is located in.	Bureau of Economic Analysis
State Income Growth	Percentage change in the total income of the target state from year *t-1* to year *t*.	Bureau of Economic Analysis

Table A2
Detailed Explanation on the Current Status of Non-compete Agreement Enforcement by State before the FTC's Non-compete Ban

This table provides detailed explanations of each state's most recent update to the non-compete statute before the April 2024 FTC's nationwide non-compete rule banning shock. Detailed descriptions for each state are obtained from the Economic Innovation Group's State Non-Compete Law Tracker (https://eig.org/state-non-compete-map/).

State Name	Legislative Restrictions	Current Status of Non-Compete Enforcement Before the FTC Ban
Alabama	Other Restrictions	Time restrictions of up to two years are presumed reasonable. Alabama statute does exempt certain professionals from non-competes, but the definition of "professionals" has been left up to the courts.
Alaska	Court Discretion	Alaska has no statutes governing non-competes. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Arizona	Other Restrictions	Arizona law bars broadcast employers from requiring their employees to sign non-competes, but the state does not have a statute governing non-compete laws generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Arkansas	Other Restrictions	While most states were trending away from the broad use of non-competes over the last decade, Arkansas was expanding their enforceability. Since the passage of Act 921 in 2015, time restrictions of up to two years are presumptively reasonable, and in some cases, non-competes may be unrestricted in geographic scope. Courts may now modify overly broad non-competes instead of striking them down in full. Employers do not need to offer their existing employees additional compensation in order to enter into a new non-compete agreement.
California	Full Ban	Non-compete agreements have long been unenforceable in California, but until recently, employers could still include them in employment contracts, which could result in a chilling effect for worker mobility. In 2023, the state legislature passed two bills strengthening the ban. Employers are now prohibited from asking their employees to sign new non-competes and must inform employees who have previously signed a non-compete that the agreements are void. Employees may pursue civil action against employers who violate the ban. The new laws also render out-of-state non-competes void within California.
Colorado	Income Restrictions	In 2022, Colorado narrowed the circumstances under which non-competes are allowed and added civil penalties for noncompliance. Non-compete agreements signed after August 2022 are only enforceable against highly compensated workers, as defined annually by the Division of Labor Standards and Statistics in the Department of Labor and Employment. Workers must meet the definition of highly compensated at both the time of signing and the time of execution. Agreements for highly compensated workers must protect trade secrets and be "no broader than is reasonably necessary" to protect legitimate business interests.
Connecticut	Other Restrictions	Connecticut has a handful of laws restricting non-competes within the healthcare, home care and broadcasting industries but does not have a statute governing non-compete laws generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Delaware	Other Restrictions	Delaware law voids any non-competes that prevent a physician from practicing medicine within a given time period or geographic area, but the state does not have a statute governing non-compete laws generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
District of Columbia	Income Restrictions	Non-compete agreements are banned for employees making less than $150,000 in 2022 dollars, adjusted annually for inflation. The ban applies to all employees who spend at least 50 percent of their working time in the district or who spend a significant percentage of their time working in the District for a DC-based employer, except casual babysitters and government workers.
Florida	Other Restrictions	Non-compete agreements should be no broader than "reasonably necessary" to protect a legitimate business interest. Time restraints of six months or less are presumed reasonable, and time restraints of greater than two years are presumed unreasonable.
Georgia	Other Restrictions	In 2010, Georgia voters approved an amendment to the constitution which allowed the state to enact the Georgia Restrictive Covenants Act expanding the enforceability of non-competes the following year. In Georgia, an employee affected by a non-compete must either regularly solicit customers or make sales, hold a management position, or otherwise act as a key employee or professional. Time restraints of up to two years are presumed to be reasonable, while time restraints greater than two years are presumed to be unreasonable.

Hawaii	Other Restrictions	Non-compete agreements must be no broader than "reasonably necessary" to protect a legitimate business interest. The non-compete may not substantially lessen competition or create a monopoly in the state.
Idaho	Other Restrictions	Non-competes may only be applied to key employees. There is a rebuttable presumption that an employee in the highest-paid five percent of the employer's employees is a key employee. Non-compete agreements may not exceed 18 months in duration without additional consideration. The non-compete must be no broader than reasonably necessary to protect a legitimate business interest.
Illinois	Income Restrictions	On January 1, 2022, Illinois' Freedom to Work Act went into effect, limiting the use of non-competes in the state. For agreements signed on or after that date, employees must work for an employer for at least two years after signing the non-compete or receive some other financial or professional benefits "adequate" to support a non-compete. The new law also added additional factors for determining whether an employer has a protectable business interest, created a schedule for increasing the state's wage threshold, and added penalties for noncompliance. Non-competes are prohibited for workers covered under the Illinois Public Labor Relations Act or the Illinois Educational Labor Relations Act. Workers terminated, laid off or furloughed as a result of the COVID-19 pandemic must be compensated in order to enforce a non-compete.
Indiana	Other Restrictions	Indiana has laws restricting the enforcement of non-competes against physicians but does not have a statute governing non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Iowa	Other Restrictions	Iowa law limits the use of non-competes against mental health professionals and workers contracted with healthcare employment agencies, but the state does not have a statute governing non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Kansas	Court Discretion	Kansas has no statutes governing non-competes. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Kentucky	Other Restrictions	Kentucky law bars healthcare services agencies from using non-competes against their temporary direct care staff, but the state does not have a statute governing non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Louisiana	Other Restrictions	Non-compete agreements are limited to two years in duration and must specify by name only the areas in which the employer conducts business.
Maine	Income Restrictions	As of September 2019, employers in Maine may not enter into non-compete agreements with workers earning at or below 400 percent of the federal poverty level. Agreements must be "reasonable" and "no broader than necessary" to protect the employer's goodwill, trade secrets, or confidential information.
Maryland	Income Restrictions	Maryland began using income restrictions on non-competes in 2019 when it voided non-competes for employees making $15 an hour. In 2023, Maryland updated the threshold to be equal to 150 percent of the state's minimum wage, which is currently $15 an hour.
Massachusetts	Other Restrictions	Non-compete agreements may not exceed 12 months in duration and must include a garden leave agreement. Non-competes are not enforceable against employees who were laid off or terminated without cause. Agreements must be "no broader than necessary" to protect a legitimate business interest.
Michigan	Court Discretion	Non-compete agreements are allowed to protect "reasonable competitive business interests," but what makes a non-compete "reasonable" and therefore enforceable is left up to the courts. Michigan courts generally find agreements lasting under one year to be reasonable and those lasting more than three years to be unreasonable.
Minnesota	Full Ban	Minnesota became the fourth state to enact a blanket ban on non-competes in 2023. The ban is not retroactive, and non-competes are still allowed in contracts related to the sale or dissolution of a business.
Mississippi	Court Discretion	Mississippi has no statutes governing non-competes. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Missouri	Other Restrictions	Missouri non-competes must protect either the employer's trade secrets or customer contacts and cannot simply prevent competition from a former employee. Non-compete agreements are presumed reasonable if they last no more than one year.
Montana	Other Restrictions	Montana allows "reasonable" non-compete agreements that protect a legitimate business interest and do not fully restrain former employees from exercising their professions.
Nebraska	Court Discretion	Nebraska has no statutes governing non-competes. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts. Nebraska courts rarely enforce non-competes based on geography and will only enforce agreements that prevent a former employee from soliciting customers that they personally did business with while working for their former employer.

Nevada	Other Restrictions	Non-competes may not be used against hourly employees. If an employee has been laid off, a non-compete agreement is only enforceable while the employer is paying the employee's salary or equivalent compensation. Agreements must be no broader than necessary to protect a legitimate business interest.
New Hampshire	Income Restrictions	Non-competes are prohibited for employees earning 200 percent or less of the minimum wage or tipped minimum wage. Employers must provide prospective employees with notice of an intended non-compete before the employee accepts an offer of employment.
New Jersey	Other Restrictions	New Jersey recently passed a law banning the inclusion of non-competes in contracts with domestic workers which will go into effect in July 2024. However, the state has no statute governing non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
New Mexico	Other Restrictions	New Mexico law voids non-competes that affect certain types of healthcare practitioners, but the state has no statute governing non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
New York	Other Restrictions	New York law restricts the use of non-competes against broadcast employees, but the state has no statute governing non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
North Carolina	Court Discretion	North Carolina statute dictates only that a non-compete agreement must be in writing. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
North Dakota	Full Ban	Non-competes in an employment context have been banned in North Dakota since 1865. Limited non-competes related to the sale of a business or dissolution of a partnership are allowed.
Ohio	Court Discretion	Ohio has no statute governing non-compete agreements. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Oklahoma	Full Ban	Non-compete agreements have been banned in Oklahoma since 1890 when the Oklahoma Territory adopted the Dakota Territory's law on non-competes. The statute has since been recodified but remains largely the same as the original law.
Oregon	Income Restrictions	Non-competes in Oregon are only enforceable if the employee's annual gross compensation exceeds $100,533 in 2021 dollars, to be adjusted for inflation annually. In order to enforce a non-compete for employees below that threshold, the employer must pay garden leave. Non-compete agreements may not exceed 12 months in duration.
Pennsylvania	Court Discretion	Pennsylvania has no statute governing non-compete agreements. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Rhode Island	Income Restrictions	Non-competes are unenforceable against workers earning 250 percent or less of the federal poverty level based on regular hours and any nonexempt workers under FLSA. They are also unenforceable against minors and short-term student interns or employees.
South Carolina	Court Discretion	South Carolina has no statute governing non-compete agreements. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
South Dakota	Other Restrictions	Non-compete agreements in South Dakota are limited to two years in duration.
Tennessee	Other Restrictions	Tennessee places statutory restrictions on the scope of non-competes for healthcare providers but has no statutes regulating non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Texas	Other Restrictions	Agreements must be no broader than "reasonable" to protect a legitimate business interest, though the definition of reasonable has been left to the courts. Physician non-competes are allowed only if they provide for a reasonable buyout and do not deny the physician access to patients that they have seen within the last year.
Utah	Other Restrictions	Non-competes signed after May 2016 are limited to one year in duration.
Vermont	Other Restrictions	Vermont law prevents cosmetology and barbering schools from signing non-competes with their students, but the state has no statutes regulating non-competes generally. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Virginia	Income Restrictions	Non-competes are banned for workers whose average weekly wage is below the average weekly wage for the commonwealth, excluding workers whose earnings come predominantly from commissions or bonuses. Employers who violate the ban will face civil penalties of $10,000 per violation.
Washington	Income Restrictions	Non-competes are not enforceable for workers earning below an inflation-adjusted salary threshold. Agreements lasting longer than 18 months are presumed unreasonable. Non-competes cannot prohibit moonlighting for workers earning less than twice the state minimum wage. Non-competes for employees who are laid off are void unless they are paid their base salary less any new earnings for the period of the agreement.

West Virginia	Court Discretion	West Virginia has no statute governing non-compete agreements. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.
Wisconsin	Court Discretion	Agreements must be "reasonably necessary" to protect a legitimate business interest, but what makes a non-compete "reasonable" and therefore enforceable is left up to the courts. Unreasonable non-competes are void in full.
Wyoming	Court Discretion	Wyoming has no statute governing non-competes. Whether a non-compete agreement is "reasonable" and therefore enforceable is left up to the courts.

Table A3
Firms' Buy-and-Hold Stock Returns around the FTC's Non-Compete Ban Proposal Announcement on January 5, 2023

This table presents 7-day buy-and-hold stock returns (BHRs) for firms headquartered in states with Full Ban, Income Restrictions, Other Restrictions, and Court Discretion on non-competes, measured around the FTC's non-compete ban proposal date of January 5, 2023. The table reports the mean BHRs for each category, as well as the differences in means between Income Restrictions, Other Restrictions, and Court Discretion relative to Full Ban, along with the corresponding *t*-values. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

	Income Restriction	Other Restriction	Court Discretion	Full Ban	Income Restriction - Full Ban	*t*-test	Other Restriction - Full Ban	*t*-test	Court Discretion - Full Ban	*t*-test
	(1)	(2)	(3)	(4)	(1) - (4)	(1) - (4)	(2) - (4)	(2) - (4)	(3) - (4)	(3) - (4)
Buy-and-Hold Returns (-3, +3)	4.873	5.857	5.257	5.428	-0.555	-1.373	0.429	1.526	-0.171	-0.323

Table A4
7-Day Cumulative Abnormal Stock Returns around the FTC's Non-compete Ban

This table reports the OLS regression results for 7-day cumulative abnormal returns. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions, and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Cumulative Abnormal Return (-3, +3)	(2) Cumulative Abnormal Return (-3, +3)	(3) Cumulative Abnormal Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)
Income Restrictions	1.776***	1.058***	1.377***	1.143***
	(0.167)	(0.225)	(0.230)	(0.247)
Other Restrictions	0.489	0.079	0.239	0.127
	(0.391)	(0.234)	(0.311)	(0.217)
Court Discretion	0.796	0.230	0.222	0.166
	(0.543)	(0.456)	(0.527)	(0.467)
Size			0.110	0.059
			(0.074)	(0.080)
Leverage			0.019***	0.003
			(0.005)	(0.005)
MTB			-0.020	-0.016
			(0.021)	(0.024)
Roa			0.062***	0.038**
			(0.017)	(0.018)
Past Return			0.009***	0.007**
			(0.003)	(0.003)
Vol			-0.010	0.002
			(0.008)	(0.008)
Illiquidity			-0.016**	-0.019**
			(0.008)	(0.008)
Industry FE	No	Yes	No	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.007	0.093	0.056	0.108

Table A5
5-Day Buy-and-Hold Stock Returns around the FTC's Non-compete Ban

This table reports the OLS regression results for 5-day buy-and-hold returns. The sample consists of 2,839 firm observations from April 19, 2024 to April 25, 2024. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions, and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-2, +2)	(2) Buy-and-Hold Return (-2, +2)	(3) Buy-and-Hold Return (-2, +2)	(4) Buy-and-Hold Return (-2, +2)
Income Restrictions	1.640***	0.974***	1.231***	1.035***
	(0.200)	(0.174)	(0.187)	(0.184)
Other Restrictions	0.590*	0.165	0.359	0.216
	(0.347)	(0.160)	(0.247)	(0.143)
Court Discretion	1.131***	0.542*	0.578*	0.483
	(0.379)	(0.279)	(0.340)	(0.287)
Size			0.177*	0.082
			(0.094)	(0.107)
Leverage			0.010*	-0.002
			(0.005)	(0.003)
MTB			-0.016	-0.008
			(0.016)	(0.018)
Roa			0.056***	0.042**
			(0.016)	(0.018)
Past Return			0.007***	0.006**
			(0.002)	(0.003)
Vol			-0.014*	-0.005
			(0.007)	(0.007)
Illiquidity			-0.011*	-0.015**
			(0.006)	(0.007)
Industry FE	No	Yes	No	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.009	0.096	0.073	0.119

Table A6
5-Day Cumulative Abnormal Stock Returns around the FTC's Non-compete Ban

This table reports the OLS regression results for 5-day cumulative abnormal returns. The sample consists of 2,839 firm observations from April 19, 2024 to April 25, 2024. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Cumulative Abnormal Return (-2, +2)	(2) Cumulative Abnormal Return (-2, +2)	(3) Cumulative Abnormal Return (-2, +2)	(4) Cumulative Abnormal Return (-2, +2)
Income Restrictions	1.570***	0.905***	1.169***	0.963***
	(0.197)	(0.163)	(0.180)	(0.172)
Other Restrictions	0.562	0.137	0.333	0.183
	(0.353)	(0.165)	(0.255)	(0.148)
Court Discretion	1.057***	0.470	0.517	0.410
	(0.385)	(0.287)	(0.348)	(0.295)
Size			0.155	0.061
			(0.093)	(0.107)
Leverage			0.010*	-0.002
			(0.005)	(0.003)
MTB			-0.016	-0.008
			(0.016)	(0.019)
Roa			0.057***	0.043**
			(0.016)	(0.018)
Past Return			0.006**	0.006**
			(0.002)	(0.003)
Vol			-0.014*	-0.005
			(0.007)	(0.007)
Illiquidity			-0.011*	-0.015**
			(0.006)	(0.007)
Industry FE	No	Yes	No	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.008	0.094	0.067	0.114

Table A7
BHRs and CARs around the FTC's Non-compete Ban: Additional Controls for State-Level Labor Market Regulations

This table reports the OLS regression results for 7-day buy-and-hold returns and cumulative abnormal returns further controlling for state-level labor market regulation. Local labor market regulation measures include the wrongful discharge laws: *Good Faith*, *Implied Contract*, *Public Policy* (e.g., Autor, Donohue, and Schwab, 2004; Acharya, Baghai, and Subramanian, 2014; Serfling, 2016) and the implementation of the Inevitable Disclosure Doctrine: *IDD*, *IDD Robust* (e.g., Klasa et al, 2018; Qiu and Wang, 2018). We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. Panel A controls the IDD implementation (*IDD*) based on Qiu and Wang (2018). Panel B controls the IDD implementation (*IDD Robust*) based on Klasa et al. (2018). Columns (1) and (3) report the regression results without firm characteristics controls. Columns (2) and (4) report the regression results with firm characteristics controls. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Panel A. Further Control for State-Level Labor Market Regulations (including IDD)

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Cumulative Abnormal Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)
Income Restrictions	0.942***	1.002***	0.821**	0.879**
	(0.331)	(0.339)	(0.330)	(0.338)
Other Restrictions	0.122	0.136	0.080	0.090
	(0.239)	(0.236)	(0.238)	(0.236)
Court Discretion	0.615	0.606	0.504	0.489
	(0.625)	(0.576)	(0.640)	(0.595)
Good Faith	-0.318	-0.372	-0.313	-0.360
	(0.315)	(0.318)	(0.317)	(0.320)
Implied Contract	0.789	0.883*	0.769	0.854*
	(0.538)	(0.476)	(0.563)	(0.502)
Public Policy	-0.024	-0.239	-0.027	-0.224
	(0.600)	(0.572)	(0.630)	(0.600)
IDD	-0.029	-0.098	-0.011	-0.068
	(0.229)	(0.251)	(0.232)	(0.254)
Size		0.085		0.064
		(0.081)		(0.080)

Leverage		0.002		0.003
		(0.005)		(0.005)
MTB		-0.015		-0.017
		(0.024)		(0.024)
Roa		0.039**		0.037*
		(0.018)		(0.019)
Past Return		0.008**		0.007**
		(0.003)		(0.003)
Vol		0.002		0.002
		(0.008)		(0.008)
Illiquidity		-0.019**		-0.019**
		(0.008)		(0.008)
Industry FE	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.098	0.115	0.094	0.109

Panel B. Further Control for State-Level Labor Market Regulations (including IDD Robust)

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Cumulative Abnormal Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)
Income Restrictions	1.046***	1.152***	0.930**	1.027**
	(0.383)	(0.391)	(0.380)	(0.389)
Other Restrictions	0.258	0.336	0.221	0.287
	(0.278)	(0.265)	(0.273)	(0.263)
Court Discretion	0.679	0.703	0.569	0.583
	(0.605)	(0.539)	(0.617)	(0.557)
Good Faith	-0.295	-0.325	-0.293	-0.320
	(0.287)	(0.284)	(0.284)	(0.281)
Implied Contract	0.617	0.646	0.587	0.614
	(0.520)	(0.456)	(0.543)	(0.480)
Public Policy	0.191	0.043	0.205	0.068
	(0.562)	(0.506)	(0.591)	(0.535)
IDD Robust	-0.277	-0.418*	-0.283	-0.404*
	(0.221)	(0.229)	(0.224)	(0.235)
Size		0.090		0.069
		(0.082)		(0.082)
Leverage		0.002		0.003
		(0.005)		(0.005)
MTB		-0.015		-0.017
		(0.024)		(0.024)

Roa		0.039**		0.037*
		(0.018)		(0.019)
Past Return		0.008**		0.007**
		(0.003)		(0.003)
Vol		0.001		0.002
		(0.008)		(0.008)
Illiquidity		-0.019**		-0.019**
		(0.008)		(0.008)
Industry FE	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.098	0.116	0.095	0.110

Table A8
BHRs and CARs around the FTC's Non-compete Ban: Additional Controls for State-Level Economic Conditions

This table reports the OLS regression results for 7-day buy-and-hold returns and cumulative abnormal returns further controlling for state-level economic conditions. Local economic conditions measures include per capita state income (*Per Capita State Income*), total state income (*Total State Income*) and total state income growth (*State Income Growth*) to capture the level of development, size, and growth perspective of the local economy (e.g., Qiu and Wang, 2018). We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. Columns (1) and (3) report the regression results without firm characteristics controls. Columns (2) and (4) report the regression results with firm characteristics controls. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Cumulative Abnormal Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)
Income Restrictions	1.449***	1.552***	1.306***	1.403***
	(0.386)	(0.411)	(0.383)	(0.406)
Other Restrictions	0.403	0.421	0.334	0.351
	(0.386)	(0.378)	(0.380)	(0.374)
Court Discretion	0.398	0.307	0.278	0.190
	(0.474)	(0.481)	(0.472)	(0.477)
Per Capita State Income	-1.062	-1.267	-1.090	-1.285
	(0.944)	(0.944)	(0.957)	(0.955)
Total State Income	0.138	0.162	0.126	0.149
	(0.170)	(0.167)	(0.168)	(0.165)
State Income Growth	-0.764	-0.633	-0.716	-0.606
	(0.821)	(0.771)	(0.799)	(0.758)
Size		0.079		0.059
		(0.081)		(0.081)
Leverage		0.002		0.003
		(0.005)		(0.005)
MTB		-0.015		-0.017
		(0.024)		(0.024)
Roa		0.040**		0.038**

		(0.018)		(0.018)
Past Return		0.008**		0.007**
		(0.003)		(0.003)
Vol		0.001		0.002
		(0.008)		(0.008)
Illiquidity		-0.019**		-0.019**
		(0.008)		(0.008)
Industry FE	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839	2,839
Adj R2	0.097	0.115	0.094	0.108

Table A9
BHRs and CARs around the FTC's Non-compete Ban: Alternative Clustering Methods

This table reports the OLS regression results for 7-day buy-and-hold returns and cumulative abnormal returns using different standard error clustering methods. The sample consists of 2,839 firm observations from April 18, 2024 to April 26, 2024. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. Columns (1) and (4) report the OLS regression results with standard errors clustering by industry. Columns (2) and (5) report the OLS regression results with standard errors clustering by industry and state. Columns (3) and (6) report the OLS regression results with standard errors bootstrapping. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)	(5) Cumulative Abnormal Return (-3, +3)	(6) Cumulative Abnormal Return (-3, +3)
Income	1.268***	1.268***	1.493***	1.143***	1.143***	1.377***
Restrictions	(0.343)	(0.283)	(0.441)	(0.320)	(0.267)	(0.424)
Other	0.171	0.171	0.281	0.127	0.127	0.239
Restrictions	(0.245)	(0.220)	(0.320)	(0.243)	(0.219)	(0.330)
Court	0.259	0.259	0.303	0.166	0.166	0.222
Discretion	(0.498)	(0.423)	(0.455)	(0.505)	(0.433)	(0.464)
Size	0.079	0.079	0.131*	0.059	0.059	0.110
	(0.090)	(0.087)	(0.073)	(0.088)	(0.085)	(0.072)
Leverage	0.002	0.002	0.019***	0.003	0.003	0.019***
	(0.010)	(0.009)	(0.006)	(0.010)	(0.009)	(0.006)
MTB	-0.015	-0.015	-0.019	-0.016	-0.016	-0.020
	(0.044)	(0.043)	(0.022)	(0.042)	(0.041)	(0.022)
Roa	0.040**	0.040***	0.063***	0.038**	0.038**	0.062***
	(0.017)	(0.013)	(0.022)	(0.018)	(0.014)	(0.022)
Past Return	0.008*	0.008*	0.010***	0.007	0.007*	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Vol	0.001	0.001	-0.010	0.002	0.002	-0.010
	(0.012)	(0.012)	(0.008)	(0.012)	(0.012)	(0.008)
Illiquidity	-0.019**	-0.019**	-0.016***	-0.019***	-0.019**	-0.016***
	(0.007)	(0.009)	(0.005)	(0.007)	(0.009)	(0.006)
Industry FE	Yes	Yes	No	Yes	Yes	No
Cluster	Industry	Industry and State	Bootstrap	Industry	Industry and State	Bootstrap
No. of Obs.	2,839	2,839	2,839	2,839	2,839	2,839
Adj R2	0.114	0.114	0.062	0.108	0.108	0.056

Table A10
BHRs and CARs around the FTC's Non-compete Ban: Excluding California

This table reports the OLS regression results for 7-day buy-and-hold returns and cumulative abnormal returns further excluding firms with headquarters located in California for a robustness check. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions and Court Discretion) according to the most recent updated statutory restrictions placed on non-compete in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. Columns (1) and (3) report the regression results without firm characteristics controls. Columns (2) and (4) report the regression results with firm characteristics controls. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Cumulative Abnormal Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)
Income Restrictions	1.484**	1.548***	1.325**	1.386**
	(0.565)	(0.573)	(0.556)	(0.565)
Other Restrictions	0.435	0.473	0.356	0.391
	(0.561)	(0.562)	(0.550)	(0.554)
Court Discretion	0.630	0.561	0.497	0.430
	(0.665)	(0.667)	(0.659)	(0.663)
Size		0.128		0.109
		(0.092)		(0.090)
Leverage		0.002		0.003
		(0.006)		(0.006)
MTB		-0.021		-0.024
		(0.030)		(0.029)
Roa		0.036		0.034
		(0.022)		(0.022)
Past Return		0.010**		0.009**
		(0.004)		(0.004)
Vol		0.001		0.002
		(0.010)		(0.010)
Illiquidity		-0.012**		-0.012**
		(0.005)		(0.005)
Industry FE	Yes	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	2,234	2,234	2,234	2,234
Adj R2	0.094	0.112	0.092	0.107

Table A11
BHRs and CARs around the FTC's Non-compete Ban: Robustness Check Without Control Variables

This table reports the OLS regression results for 7-day buy-and-hold returns and cumulative abnormal returns further without control variables. The sample consists of 4,620 firm observations from April 18, 2024 to April 26, 2024. We sort firms into four broad categories and generate indicator variables for each category (including Full Ban, Income Restrictions, Other Restrictions and Court Discretion) according to the most recent updated statutory restrictions placed on non-competes in each firm's headquarters state before the FTC's nationwide ban on non-competes. We set the full ban group as the reference group in regressions. Columns (1) and (2) report the regression results on BHRs with and without industry fixed effects. Columns (3) and (4) report the regression results on CARs with and without industry fixed effects. A summary table of the primary statute for each headquarters state is provided in Table 1. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Cumulative Abnormal Return (-3, +3)	(4) Cumulative Abnormal Return (-3, +3)
Income Restrictions	1.392***	0.815***	1.289***	0.724***
	(0.161)	(0.191)	(0.172)	(0.199)
Other Restrictions	0.766***	0.367**	0.710***	0.319*
	(0.262)	(0.167)	(0.264)	(0.169)
Court Discretion	0.978***	0.410	0.877**	0.316
	(0.357)	(0.280)	(0.373)	(0.295)
Firm-level Controls	No	No	No	No
Industry FE	No	Yes	No	Yes
State Cluster	Yes	Yes	Yes	Yes
No. of Obs.	4,620	4,615	4,620	4,615
Adj R2	0.004	0.070	0.004	0.070

Table A12
BHRs around the FTC's Non-compete Ban: Robustness Check for State-level Covenants-not-to-Compete Enforcement Index

This table reports the OLS regression results for 7-day buy-and-hold returns and various state-level covenants-not-to-compete enforcement index (NC Index) variables as a robustness check. The state-level covenants-not-to-compete enforcement index follows Bai, Eldemire, and Serfling (2024). We use various covenants-not-to-compete enforcement index variables to replace the main indicator variables in Table 3. Column (1) uses *NC Index Above Zero* as an indicator equal to one if the state-level covenants-not-to-compete enforcement index is larger than zero. Column (2) uses *NC Index Above One* as an indicator equal to one if the state-level covenants-not-to-compete enforcement index is larger than one. Column (3) uses *NC Index Above Two* as an indicator equal to one if the state-level covenants-not-to-compete enforcement index is larger than two. Standard errors are clustered at the state level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Table A1 in the Online Appendix.

Variables	(1) Buy-and-Hold Return (-3, +3)	(2) Buy-and-Hold Return (-3, +3)	(3) Buy-and-Hold Return (-3, +3)
NC Index Above Zero	0.390*		
	(0.217)		
NC Index Above One		0.472**	
		(0.226)	
NC Index Above Two			0.405*
			(0.214)
Size	0.091	0.092	0.091
	(0.079)	(0.079)	(0.079)
Leverage	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)
MTB	-0.014	-0.013	-0.014
	(0.024)	(0.024)	(0.024)
Roa	0.040**	0.040**	0.040**
	(0.018)	(0.018)	(0.018)
Past Return	0.008**	0.008**	0.008**
	(0.003)	(0.003)	(0.003)
Vol	0.001	0.002	0.002
	(0.008)	(0.008)	(0.008)
Illiquidity	-0.018**	-0.018**	-0.018**

	(0.008)	(0.008)	(0.008)
Industry FE	Yes	Yes	Yes
State Cluster	Yes	Yes	Yes
No. of Obs.	2,839	2,839	2,839
Adj R2	0.111	0.111	0.111