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From Shares to Machines: How Common Ownership Drives Automation

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From Shares to Machines: How Common Ownership Drives Automation

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Abstract

We study whether common ownership affects the direction of technological change. We develop a task-based model with multiple local labor markets in which commonly owned firms internalize wage externalities from portfolio rivals when hiring from the same labor pool, increasing incentives to automate. We establish causality by exploiting institutional investor mergers in a dynamic DiD design, using U.S. data on institutional ownership, establishment level employment, and text-classified automation patents. Increases in common ownership among local labor-market rivals raise firms' automation propensity by 22.7 percentage points and reduce employment growth. The effect disappears when firms do not compete within labor markets.

Keywords: Common Ownership, Automation, Local Labor Markets, Market Power.

JEL Codes: O33, G23, J42,

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1 Introduction

Economic growth depends not only on how much firms innovate, but also on the *direction* in which they choose to innovate. When investing in R&D, firms face a fundamental choice: develop new products, or improve their production processes for existing products. Among process innovations, few decisions are as consequential as the choice between labor-augmenting technologies—which complement workers and enhance their productivity—and automation technologies that replace labor with machines and software. These choices shape employment dynamics, the income distribution, the pace of technological progress, and, ultimately, aggregate economic growth.

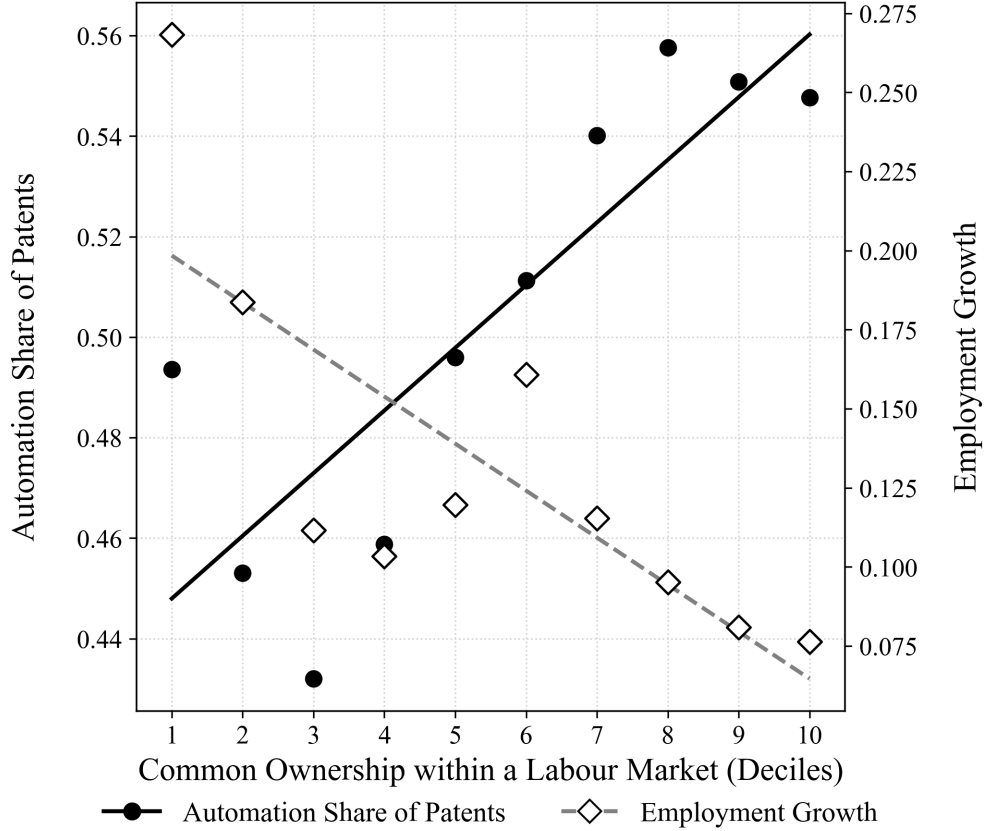
What guides firms’ decisions to invest in automation technologies? Recent evidence highlights substantial heterogeneity in automation and AI adoption across firms, reflecting differences in capabilities, complementary inputs, and financing (Acemoglu et al., 2020; McElheran et al., 2023; Babina et al., 2024). We propose a new determinant arising when firms share *common owners*. In this setting, a firm’s innovation decisions are shaped not only by its own profit-maximising considerations but also by the performance of other firms within its owners’ portfolio, particularly competitors operating in the same labor markets. This channel matters quantitatively as common ownership has expanded dramatically over recent decades.¹

This paper examines the connection between firms’ ownership structures and the direction of technological change. Specifically, we ask: Does ownership overlap influence a firm’s choice to innovate in order to automate its production? If so, what are the implications for firm employment growth? We address these questions both theoretically and empirically. First, we develop a task-based model of automation with common ownership and multiple local labor markets. We show that when firms share owners and draw labor from the same labor market, they automate more. Conversely, ownership overlap does not have any effect on automation when firms operate in separate labor markets.

Second, we test these predictions using data on U.S. public firms. We construct firm-level common ownership measures from institutional investors’ holdings reported in Thomson Reuters and get firms’ financial information from COMPUSTAT. We map firms’ spatial distribution of employment across commuting zones using establishment-level (NETS) data, allowing us to identify which firms compete for labor. We measure automation innovation by classifying patents into automation and non-automation technologies using a text-based

¹Backus et al. (2021) document that common ownership has tripled among firms in the S&P 500 in the past decades. Eldar and Grennan (2021) show a similar trend for VC-held start-ups. Additionally, the 10 largest institutional investors have quadrupled their ownership of U.S. stocks; by the end of 2016, they managed 26.5% of total equity assets (Ben-David et al., 2016).

Figure 1
FIRM LEVEL EMPLOYMENT GROWTH AND AUTOMATION BY COMMON OWNERSHIP



Notes: A comparison of the share of automation patents to total patents and employment growth rates across deciles of common ownership of firms with other firms operating in the same commuting zones. The automation share is defined as the number of automation patents divided by total patents. The figure winsorizes the measure of common ownership within local labor markets for the top 1% to improve readability, given the highly right-skewed nature of the variable. Automation patents are classified using a text-based method (Mann and Püttmann, 2021). Employment growth is defined as $(emp_{it} - emp_{it-1}) / (emp_{it-1})$ using data from Compustat.

classification method (Mann and Püttmann, 2021). Figure 1 provides evidence in the raw data: firms with higher common ownership among local labor market rivals produce a greater share of automation patents and exhibit slower employment growth.

We establish causality using mergers between institutional investors as a quasi-natural experiment. These mergers plausibly generate exogenous shifts in the level of common ownership across firms, but are unlikely to select onto firms in anticipation of a change in their automation rate (He and Huang, 2017; Lewellen and Lowry, 2021). Since many firms experience increases in common ownership due to such mergers several times throughout our sample, we apply state-of-the-art dynamic *difference-in-differences* (DID) methods developed by De Chaisemartin and d’Haultfoeuille (2024). Additionally, we develop a continuous

treatment framework for common ownership, since mergers among institutional investors affect firms heterogeneously depending on the merger partners’ (pre-merger) ownership shares. Moreover, in this setup, establishment-level information on the distribution of a firm’s labor force allows us to disentangle the effects of common ownership on our outcome variables, separately for scenarios with and without labor-market rivalry between portfolio firms. Therefore, we can estimate the impact of increases in common ownership among firms depending on whether they compete in labor markets.

We find that firms that experience an increase in common ownership with other firms operating in the same local labor market (i.e., in at least one shared commuting zone) increase patent output on automation technologies. Quantitatively, our results indicate that the average treated firm increases its propensity to patent an automation technology by approximately 53% (22 p.p.). Simultaneously, we document a decrease in employment growth for these firms. In contrast, we find no significant effect of common ownership between firms operating in distinct labor markets on a given firm’s automation rate or employment growth. Hence, our empirical results show that common ownership between institutional investors of labor-market competitors steers technological progress toward automation, consistent with our theoretical model.

Our model makes the mechanism explicit. An increase in common ownership raises the extent to which a firm internalizes the profits of other firms held in its owners’ portfolios. When two firms operate in the same local labor market, hiring an additional worker by one firm increases equilibrium wages for both. As common ownership intensifies, each firm places greater weight on this wage externality: the cost of expanding employment is no longer limited to its own wage bill but includes the induced increase in labor costs for its commonly owned rivals. This heightened internalization strengthens the incentive to develop and adopt labor-saving technologies that curb labor demand—or slow its growth—within the shared labor market. By contrast, when firms operate in distinct labor markets, wages are determined locally and do not generate cross-firm externalities; in such cases, higher common ownership does not alter automation incentives.

Our findings are robust to alternative measures of automation innovation. The most significant of these being to show that the firms are indeed innovating to automate their production process, instead of, for example, creating consumer goods. We do so by interacting our measure of automation innovation with a measure of product and process patents developed by [Bena and Simintzi \(2024\)](#). We also find that our results hold given alternative treatment designs, to restricting the sample to the pre-2007 period, and to using a traditional binary treatment specification, consistently showing that increases in common ownership among labor-market rivals cause firms to innovate to automate.

The structure of the paper is as follows. The remaining part of this section discusses the literature and our contributions. Section 2 outlines the model and develops testable hypotheses. Section 3 presents our empirical strategy, providing a detailed description of the data used and their sources, as well as reporting the results. Finally, Section 4 offers concluding remarks.

Related Literature We contribute to a broad literature that studies firms’ innovation decisions, with particular attention to the distortions and frictions that influence not only how much firms innovate, but also the direction and composition of their innovative effort. A central building block of this literature is the Schumpeterian growth framework, in which innovation arises from incumbents and entrants engaging in creative destruction. Foundational contributions include [Aghion and Howitt \(1992\)](#), who formalize the process of creative destruction; [Klette and Kortum \(2004\)](#), who embed heterogeneous firms and quality ladders to match micro-level innovation patterns; and subsequent work showing how market structure, competition, and policy shape firms’ innovation incentives ([Aghion et al., 2005](#); [Aghion et al., 2015](#)). This body of research highlights that firms face multiple margins of innovation choice, and that distortions—arising from market power, financial constraints, corporate governance, or policy—may shift not only the amount of innovation but also its direction.

[Acemoglu and Restrepo \(2018\)](#) formalize the fundamental trade-off between automation and labor-augmenting technologies, showing how institutional and economic conditions shape firms’ incentives to automate tasks.² [Akcigit et al. \(2021\)](#) study firms’ allocation between basic and applied research and show how policy influences the composition of innovative activity. Other contributions focus on additional margins of innovation choice: for instance, [Acemoglu et al. \(2018\)](#) distinguish between radical and incremental innovation, while [Akcigit et al. \(2023\)](#) analyze how political connections distort firms’ innovation portfolios. Collectively, this literature demonstrates that firms’ innovation direction is shaped by both technological opportunities and institutional or competitive frictions. We contribute to the literature by identifying an additional mechanism that leads firms to increase their automation effort. That is, we show that part of the surge in firms’ investments in automation technologies is the result of common ownership among local labor-market rivals. Common

²Related empirical work also points to an important role of labor-market conditions in shaping the direction of innovation. [Danzer et al. \(2024\)](#) show that exogenous increases in low-skilled labor supply reduce automation innovation, with effects concentrated in process-related automation patenting, while finding no corresponding effect on non-automation patents. More broadly, [Terry et al. \(2026\)](#) show that immigration increases local innovation and wage growth over time, underscoring that shocks to local labor markets can have important effects on firms’ innovative activity.

ownership leads firms to internalize the negative externality of employing workers on the rivals’ wage bill. Thus, common ownership in local labor markets increases the incentives to invest in innovation that allows firms to save labor through the automation of tasks. Hence, automation that is driven by common ownership instead of other motives such as firm growth or improving productivity could lead to a more negative relationship between automation and labor-market outcomes, such as wages, employment, and the labor share of income, and exacerbate the potential problem of “*excessive automation*” (Acemoglu et al., 2020; Santini, 2025).

Second, our paper contributes to the debate on how common ownership shapes firms’ objective functions and behavior. A large literature studies its implications for product-market competition, consumer welfare, and antitrust policy (Baker, 2015; Posner et al., 2016; Azar et al., Backus et al., 2021). In the context of innovation, López and Vives (2019) show that common ownership can increase R&D when firms internalize positive technology spillovers, while Anton et al. (2018) demonstrate that its overall effect depends on the balance between technological spillovers and product-market rivalry. We extend this literature by shifting the focus from the *level* of innovation to its *direction*. In our setting, increases in common ownership among firms that compete in the same local labor market lead to a significant rise in automation patenting. In contrast, non-automation patenting, and in particular product innovation, remains largely unchanged. Thus, we interpret our results as complementing those of Anton et al. (2018). In particular, while their framework focuses on the innovation effects of product-market rivalry and technological spillovers, our evidence suggests that common ownership can also affect innovation through the internalization of labor-market externalities, thereby shifting its direction toward labor-saving technologies.³ At the same time, to the extent that automation technologies generate spillovers across labor-market rivals, such spillovers may further amplify the effects we document.

2 Theory

In this section, we present a simple model that we employ to derive testable empirical hypotheses. Mathematical derivations are relegated to the appendix (Section A).

³In our empirical analysis, we do not explicitly condition on firms’ proximity in technological or product-market space. The absence of an effect on non-automation and product-innovation patenting may thus arise because positive technology-spillover effects and negative product-market rivalry effects offset each other on average in our sample.

2.1 The model

Consider an economy with a set of firms, $\mathcal{J} = \{1, \dots, j, \dots, J\}$, and a set of local labor markets, $\mathcal{C} = \{1, \dots, c, \dots, C\}$. We refer to one of the firms as the focal firm, f , and analyze its automation strategy. Firm f operates its production process in a subset $\mathcal{C}_f \subset \mathcal{C}$.⁴ We say that a different firm j has labor-market (LM) overlap with the focal firm f if both employ production plants in some labor market at the same time, i.e., there exists some location $c \in \mathcal{C}_f \cap \mathcal{C}_j$.

Given the geographic distribution of firm f 's production sites, we can partition the set of the remaining $J - 1$ firms in the economy into two subsets. Namely, the set $\mathcal{R}_f$, such that a firm $j \in \mathcal{R}_f$ has LM overlap with firm f , and the set $\mathcal{N}_f$, such that if $j' \in \mathcal{N}_f$, then we have $\mathcal{C}_f \cap \mathcal{C}_{j'} = \emptyset$.

We assume that firm f has *labor market power* in the local labor markets in which it operates, $\mathcal{C}_f$. To model this most simply, we assume that the focal firm f has full knowledge of the labor supply structure and takes into account that

$$\frac{\partial w^c}{\partial L_f^c} > 0,$$

where L_f^c is firm f 's labor demand in c and w^c the wage firms have to pay in labor market c to employ labor. Hence, if firm f increases its labor demand in one of its plants, it raises workers' outside options in the locations where this plant is located. Therefore, we call the firms in $\mathcal{R}_f$ firm f 's labor-market rivals and, conversely, there is no labor market rivalry between f and firms in $\mathcal{N}_f$.

We abstract from wage spillover effects between labor markets. In particular, this implies that firm f cannot affect the wage that other firms pay in a location $c' \notin \mathcal{C}_f$, in which it does not operate, i.e., $\partial w^{c'} / \partial L_f^c = 0$.

For simplicity, we abstract from product market competition, and all firms are price takers in the capital market.⁵ We can think about the firms as multi-product firms producing different goods Y_j^c in each establishment (or labor market) and selling them to a global market at a given price p_j^c , such that they do not have price-setting power in their respective product markets.

There is a collection of institutional investors that hold shares in the firms. Drawing on the literature suggesting that good corporate governance induces management to maximize

⁴In the empirical analysis, we interpret the labor markets as commuting zones. We consider the geographic distribution of firms' production plants as exogenous.

⁵For a model with product market competition, see [Hutschenreiter and Santini \(2021\)](#), in which the effect of common ownership on automation depends on the ratio of factor supply elasticities. In the case in which capital supply is more elastic than labor supply, common ownership leads to an increase in automation.

a weighted average of investors' cash flows from their portfolios, we posit that, with common ownership, firm f 's objective function internalizes the effects of its strategic decisions on the profits of other portfolio firms. As shown by [López and Vives \(2019\)](#), we can thus write firm f 's objective function as

$$\phi_f = \pi_f + \sum_{j \neq f}^J \lambda_{fj} \pi_j, \quad (1)$$

where π_f and π_j are the profit functions of firms f and j , respectively, and $\lambda_{fj} \geq 0$ is the profit weight firm f puts on firm j 's profits. The parameter λ_{fj} is a function of the cashflow rights of firm f 's investors to the profits of firms f and j . In particular, λ_{fj} increases in the degree of ownership overlap of the two firms. Thus, an increase in common ownership between the two firms is modeled as an increase in λ_{fj} in our analysis.

At each location $c \in \mathcal{C}_f$, firm f produces output Y_f^c using a technology that requires the performance of a continuum of tasks $x \in [0, 1]$. The final output of firm f in location c is given by the following production function:

$$Y_f^c = \exp \left(\int_0^1 \ln [y_f^c(x)] dx \right)^\nu, \quad (2)$$

where $y_f^c(x)$ is the quantity of task x employed in production, and $\nu < 1$ is the degree of return to scale.⁶ Each task is in turn produced according to the following production function,

$$y_f^c(x) = \gamma_m(x) m_f^c(x) + \gamma_\ell(x) \ell_f^c(x), \quad (3)$$

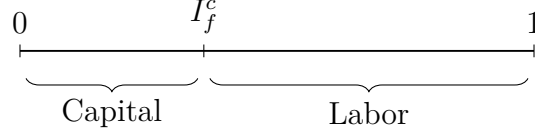
in which quantities of machines $m_f^c(x)$ and labor $\ell_f^c(x)$ are perfect substitutes, and $\gamma_m(x)$ and $\gamma_\ell(x)$ are the productivity schedules of capital and labor over the task, which are identical across locations. Without loss of generality, we assume that at each production site of firm f in the locations, $c \in \mathcal{C}_f$, the productivity schedules are continuously differentiable and the set of tasks is ordered in such a way that the comparative advantage of producing a task with labor strictly increases in x , i.e.,

$$\frac{d}{dx} \left(\frac{\gamma_\ell(x)}{\gamma_m(x)} \right) > 0. \quad (4)$$

Given the task production function in (3) and the assumption in (4) regarding the comparative advantage structure between capital and labor, the unit measure of tasks is optimally

⁶Empirical estimates generally support decreasing returns at the firm level. See, for instance, [Basu and Fernald \(1997\)](#). The assumption $\nu < 1$ ensures strict concavity of the firm's objective function and therefore guarantees a well-behaved optimization problem. Alternatively, the same role could be played by a downward-sloping product demand.

Figure 2
TASK ALLOCATION



Notes: Allocation of capital and labor to tasks by firm f 's plant in location c .

divided into two regions: the tasks produced with capital and the tasks performed by labor. A diagram of this allocation is shown in Figure 2. The threshold separating these two sets is denoted by I_f^c . Therefore, I_f^c naturally admits an interpretation as the *degree of automation* of firm f 's plant in location c , with a larger cutoff corresponding to a larger share of tasks performed by capital. Despite having access to identical technology across establishments (or local labor markets), the degree of automation may vary across locations—for example, because of different levels of “local” common ownership. Accordingly, firm f 's average degree of automation is given by

$$I_f \equiv \frac{1}{|\mathcal{C}_f|} \sum_{c \in \mathcal{C}_f} I_f^c. \quad (5)$$

and the level of total employment of firm f is

$$L_f \equiv \sum_{c \in \mathcal{C}_f} L_f^c. \quad (6)$$

Finally, to maximize its objective function, firm f solves the following problem:

$$\begin{aligned} \max_{\Omega_f} \quad & \sum_{c \in \mathcal{C}_f} \left[p_f^c Y_f^c - r K_f^c - w^c L_f^c + \sum_{j \neq f: c \in \mathcal{C}_j} \lambda_{fj} (p_j^c Y_j^c - r K_j^c - w^c L_j^c) \right] \\ \text{s.t.} \quad & Y_f^c = \exp \left(\int_0^1 \ln [y_f^c(x)] dx \right)^\nu, \\ & y_f^c(x) = \gamma_m(x) m_f^c(x) + \gamma_\ell(x) \ell_f^c(x), \\ & K_f^c = \int_0^{I_f^c} m_f^c(x) dx, \\ & L_f^c = \int_{I_f^c}^1 \ell_f^c(x) dx. \end{aligned}$$

where firm f 's choice set is

$$\Omega_f = \left\{ \left(Y_f^c, K_f^c, L_f^c, I_f^c, \{y_f^c(x), m_f^c(x), \ell_f^c(x)\}_{x \in [0,1]} \right) \right\}_{c \in \mathcal{C}_f}.$$

By combining the first-order conditions of the maximization problem, we can show that

the optimal degree of automation in location c is characterized by the following condition:⁷

$$\frac{\gamma_\ell(I_f^c)}{\gamma_m(I_f^c)} = \frac{W_f^c}{r}, \quad (7)$$

where W_f^c denotes the *perceived* marginal cost of labor faced by firm f in local labor market c . Under assumption (4), equation (7) implies that an increase in the marginal cost of labor raises the optimal level of automation.⁸ Since firms take the rental rate of capital r as given in the capital market, automation decisions are driven by the perceived marginal cost of labor W_f^c . We characterize its determinants in the following equation:

$$W_f^c = w^c + \frac{\partial w^c}{\partial L_f^c} L_f^c + \sum_{j \neq f: c \in \mathcal{C}_j} \lambda_{fj} \frac{\partial w^c}{\partial L_f^c} L_j^c. \quad (8)$$

Before commenting on the relationship in (8) and elaborating on the intuition regarding the effect of common ownership on automation, we state the main theoretical result of the paper. Specifically, we analyze the relationship between the degree of common ownership—represented by the profit weight λ_{fj} —and the focal firm’s optimal average level of automation, I_f , and employment, L_f .

An increase in common ownership (profit weight λ_{fj}) between firm f and a labor-market rival $j \in \mathcal{R}_f$ leads to an increase in the focal firm’s average level of automation I_f and a decrease in its level of employment L_f .

Proof. See Theoretical Appendix A. □

To understand the intuition behind this result, consider the decomposition in (8). Absent labor market power, automation depends solely on the local wage w^c , which the firm takes as given. However, when the firm possesses monopsony power, two additional strategic components emerge. The second term, $\frac{\partial w^c}{\partial L_f^c} L_f^c$, exists even in the absence of common ownership; it captures the firm’s baseline incentive to automate to mitigate the upward pressure that its own hiring exerts on its wage bill. The third term, $\sum_{j \neq f: c \in \mathcal{C}_j} \lambda_{fj} \frac{\partial w^c}{\partial L_f^c} L_j^c$, represents the core interaction between labor market power and common ownership. When $\lambda_{fj} > 0$, the focal firm internalizes how its labor demand affects the costs of other firms in its owners’ portfolios. This creates an additional incentive to automate that exceeds what labor market power alone would dictate.

⁷Refer to Appendix A for the detailed derivation.

⁸Given the assumed relationship between the productivity schedules in (4), an increase in the right-hand side can be matched on the left-hand side only through a higher automation intensity I_f^c .

Consequently, as common ownership with a labor-market rival intensifies, firm f increasingly internalizes the rival's profit. Since firm f can only influence the profits of $j \in \mathcal{R}_f$ by reducing that rival's wage bill, it chooses to restrict its own labor demand in the shared locations $c \in \mathcal{C}_f \cap \mathcal{C}_j$. Effectively, the firm trades off the marginal cost of reducing its own production against the marginal benefit of lowering labor costs for its commonly owned peers. To mitigate the resulting loss in output, the firm substitutes labor for capital, shifting the automation threshold I_f^c toward higher-indexed tasks, thereby raising the average degree of automation, I_f . Thus, a positive shock to common ownership among local rivals induces the firm to expand its automation beyond its ex ante optimal level.

This mechanism hinges entirely on the firm's ability to influence a rival's wage bill through its own labor demand. This leads directly to our next result:

Common ownership between firm f and a firm $j' \in \mathcal{N}_f$ (no labor-market overlap) has no effect on firm f 's optimal degree of automation I_f or employment L_f .

Proof. The result follows from the fact that firm f cannot influence the wage bill of firm j' . Since the profits of j' are independent of firm f 's strategic choices, the internalization of those profits does not alter firm f 's marginal incentives. $\square$

In the next subsection, we map the model's theoretical implications into a set of testable hypotheses suitable for empirical analysis.⁹

2.2 Hypothesis development

In this section, we translate the theoretical results into testable empirical hypotheses. Drawing on Proposition 2.1, we have seen that a necessary condition for common ownership to alter firms' automation strategies is that firms have some degree of market power in the labor market. In particular, our mechanism requires that the focal firm, whose automation choice we observe, can influence the wage bill of the other portfolio firms with which it shares common owners. Therefore, in our empirical analysis, we will distinguish between firms that interact in the same local labor markets and those that operate in distinct labor markets. To this end, we define labor market rivals as those with concurrent employment in the same commuting zones. In particular, we say that firms are local labor market competitors if they both have positive employment in establishments located in at least one shared commuting zone simultaneously. Furthermore, we use a classification of patents into automation and non-automation categories based on patent texts to measure the automation content of firms'

⁹In the Theoretical Appendix A, we show that common ownership increases automation even in a model where firms internalize the strategic responses of other firms, i.e., under a Nash equilibrium.

innovation output. Then, given the result in proposition 2.1, we test the following hypothesis: An increase in common ownership with local labor market rivals *causes* the focal firm to increase the automation content of its innovation output, and decrease its employment growth.

From our model, we expect to observe an increase in automation if the overlap in ownership between firms in the same local labor markets increases. Thus, following a positive shock to common ownership, a firm is likely to increase its degree of automation through innovation. Furthermore, as Corollary 2.1 states, we expect the effect of common ownership to be absent if we consider the overlap in ownership of the focal firm with those firms in the investors' portfolios unaffected by the focal firm's labor demand decisions. Thus, we expect that an increase in common ownership among firms that do not operate in the same labor markets does not increase the automation content of firms' innovation output. Hence, we test the following hypothesis: An increase in common ownership among firms employing labor in different commuting zones does not cause the focal firm to increase automation innovation or decrease its employment growth.

3 Empirical Analysis

We bring both of these hypotheses to the data to test the implications derived from the model. In this section, we discuss the data sources, the variables, and our identification strategy. Finally, we report the empirical findings.

3.1 Data Sources

We build a novel data set that combines eight different data sources: (i) We start by retrieving firms' financial information from COMPUSTAT; (ii) we merge this information with the number of outstanding shares and stock prices from CRSP; (iii) Thomson Reuters form 13F file provides firms' institutional shareholder information, i.e., the institutional investors and the number of outstanding shares owned by each of them; (iv) We gather data on the geographic distribution of firms' labor force from the establishment-level NETS database for each county and map them to US commuting zones that we define as local labor markets; (v) We use patent information from the USPTO and the DISCERN database ([Arora et al., 2021](#)) that provides us with a match of patents to public corporations; and (vi) we obtain M&A data from [Lewellen and Lowry \(2021\)](#) for mergers between institutional investors. (vii) We use the classification built in [Mann and Püttmann \(2021\)](#) of USPTO patents as either automation or non-automation patents. Finally, (viii) we use the process patent claim-level

classification from [Bena and Simintzi \(2024\)](#). We now explicitly define the variables used in our empirical analysis.

3.2 Variables

3.2.1 Common Ownership

We measure common ownership using the *Cindex* ([Lewellen and Lowry, 2021](#)). For firm f at time t , common ownership is defined as

$$Cindex_{ft} = \frac{1}{J} \sum_{j=1}^J \sum_{i=1}^I \beta_{if} \beta_{ij}, \quad (9)$$

where $i = 1, \dots, I$ indexes institutional investors and $j = 1, \dots, J$ indexes the relevant set of firms. The terms β_{if} and β_{ij} denote the fractions of outstanding shares of firms f and j , respectively, held by investor i at the calendar year-end.

The firm set j includes either local labor market rivals—firms operating in at least one commuting zone also served by f —or firms operating in commuting zones that do not overlap with those of f . To capture these distinctions, we construct $CindexLM_{ft}$ by restricting j to firms with labor-market overlap and $CindexNotLM_{ft}$ by restricting j to firms in disjoint commuting zones.

3.2.2 Automation Patents

For our empirical analysis, we need a dynamic measure of automation at the firm level. To this end, we use the data provided by [Mann and Püttmann \(2021\)](#). This paper defines automation as a “*device that carries out a process independently*”. Using this definition, they train a classification model on patent texts to classify all USPTO patents awarded between 1976 and 2014 as either an automation innovation or not.¹⁰ Table 1 gives examples taken from the original paper of both innovation types. In short, the authors train a naïve Bayes classifier. They define two patent classes: automation and non-automation. They first manually classify 560 patents into both classes and, using the mutual information criterion, define a set of words informative about each class. Words that identify that a patent is an automation device are *automat*, *output*, *execut*, *inform*, *input*, and *detect*.¹¹ The algorithm then uses the occurrence of these words to calculate a probability that the patent belongs to

¹⁰The paper restricts the sample to utility patents and therefore doesn’t classify design patents; however, as these do not “carry out” a process, their comparison would introduce noise in our analysis.

¹¹These words are stemmed first, to capture variations of the same word, for example, automation, automate, and automatic all stem from the word automat.

Table 1
EXAMPLE AUTOMATION PATENTS

Patent title	Patent number	Automation?
“Automatic taco machine”	5531156	Yes
“Automated email activity management”	7412483	Yes
“Hair dye applicator”	6357449	Yes
“Bicycle frame with device cavity”	7878521	No
“Process for making pyridine-thione salts”	4323683	No
“Golf ball”	4173345	No

Notes: This table shows examples of patents’ classification into automation or non-automation patents. Table taken directly from [Mann and Püttmann \(2021\)](#).

each class, and by taking the maximum, they classify each patent.

The authors present the standard validation tests. In the training sample, the algorithm and manual coding agree 80% of the time, and the probabilities of a false positive (type-1) and a false negative (type-2) are 21% and 17%, respectively. For the out-of-sample testing, performance declines slightly. However, performance remains satisfactory, with true positives, false positives, and false negatives of 77%, 23%, and 22%, respectively.

Using this broad definition of automation, combined with the machine learning algorithm, allows us to measure automation for a large sample of firms across industries and time. While classification errors introduce noise, as long as there is no systematic bias in the occurrence of type-1 and type-2 errors, we believe the measure provides a valuable source of information on firm automation strategies.

Based on this patent-level classification, we construct several firm-year measures of automation innovation that allow us to track changes in firms’ automation strategies over time. Our primary measure is *AutoDummy*, an indicator equal to one if a firm files, in a given year, a patent application that is subsequently granted and classified as an automation patent according to [Mann and Püttmann \(2021\)](#), and zero otherwise. We use this variable to capture changes in firms’ propensity to engage in automation-related technological innovation.

We additionally construct measures capturing the extensive margins of firms’ automation activity. Specifically, we define *lnAuto* and *lnNonAuto* as the natural logarithms of one plus the number of automation and non-automation patents filed by the firm in a given year, respectively.

To assess the relative emphasis on automation within firms’ broader innovation portfolios, we define *AutoRatio* as the difference between *lnAuto* and *lnNonAuto*. This measure captures the extent to which firms prioritize automation-related innovation relative to other inventive activities, thereby allowing us to examine shifts in the automation content of firms’ overall

Table 2
AUTOMATION AND PROCESS PATENTS

Automation Patent	Process Patent		Total
	0	1	
0	289,175	308,161	597,336
1	184,951	490,052	675,003
Total	474,126	798,213	1,272,339

Notes: Contingency table of automation and process patents on a sample of patents matching [Mann and Püttmann \(2021\)](#) and [Bena and Simintzi \(2024\)](#) into the [Arora et al. \(2021\)](#) database, from which we construct our firm-year panel. Process patents are classified as those for which [Bena and Simintzi \(2024\)](#) classify at least one of the patent’s claims as a process claim.

innovation strategies beyond changes in the total volume of patenting.

Finally, to account for heterogeneity in patent quality, we compute citation-weighted versions of both automation and non-automation innovation measures. To correct for citation truncation, we normalize each patent’s citation count by the average number of citations received by patents in the same technology class and application year, following [Hall et al. \(2001\)](#) and [Atanassov \(2013\)](#).

3.2.3 Process Patents

We extend our measure of automation to patents that directly target the production process by examining the firm’s choice to produce process patents that automate production, as opposed to automation product patents. Each patent granted by the USPTO contains a number of claims. These are unique features of the innovation, each covered by the intellectual property rights of the patent. [Bena and Simintzi \(2024\)](#), classify each of a patent’s claims as product or process claims. A process innovation describes a new way to produce an existing good, while a product innovation typically describes a new good that did not exist before.

The authors claim that the category of the invention is almost always explicitly mentioned in the first section of each patent claim in a direct and unambiguous way. The authors categorize each claim as a process or product claim by examining the claim preamble for a set of keywords. This provides a measure at the claim level, which we aggregate to the patent level by tagging patents that produce at least one process claim as having made a process innovation. Many patents which do claim process innovations also claim product innovations, however this threshold ensures that our definition of product patents make no innovation on a production process.

Table 3
AUTOMATION AND PROCESS PATENTS EXAMPLES

Automation × Process
Method of tracking automotive production <i>Ford Motor Company</i> — US7394371 Automatically tracks each vehicle and its build status as it moves through a car factory.
Automation × Product
Autonomous floor-cleaning robot <i>iRobot Corp</i> — US6883201 A self-driving floor cleaner that adjusts its scrubbing and vacuuming as it cleans.
Non-automation × Process
Purification of silicon <i>Westinghouse Electric</i> — US4428917 A multi-step manufacturing method for producing high-purity low-cost silicon.
Non-automation × Product
Disposable undergarment <i>Johnson & Johnson</i> — US4205679 A disposable training/incontinence undergarment, commonly referred to as a diaper.

Notes: Examples of patents by automation and product/process type. Each patent lists the title, assignee, U.S. patent number and a short summary provided for brevity. These examples are taken from a data set built by merging Mann and Püttmann (2021) and Bena and Simintzi (2024) into the Arora et al. (2021) database.

Table 2 shows the joint distribution of automation and process patents. Automation patents are over 2.66 times as likely to be a process patent and target a production process than patenting a new product. Non-automation patents, on the other hand, are relatively balanced across process and product patents in this sample. Table 3 presents examples for each category of patents.

3.2.4 Employment Growth

Since our model predicts that common ownership increases automation due to a labor market channel, we also test if common ownership leads firms to change their hiring behavior. We measure the growth rate of firm-level employment, that is,

$$EmpGrowth_{ft} = \log(Employees_{ft}) - \log(Employees_{ft-1}) \quad (10)$$

where $Employees_{ft}$ is the number of employees of a firm in year t .

3.2.5 Treatment variables

Following the recent literature on common ownership and the estimation of its causal effects (Lewellen and Lowry, 2021), we exploit exogenous variation in common ownership arising from mergers between institutional investors. We draw on information on 53 institutional mergers occurring between 1990 and 2010. To construct a set of continuous and discrete treatment variables we use the merging parties’ ownership stakes in the universe of publicly traded companies in the quarter preceding the merger announcement date.¹²

We begin by introducing the notation required to define the treatment sets and construct the treatment variables. Let $\mathbf{M}_t = \{1, \dots, m, \dots, M_t\}$ denote the set of mergers occurring at time t , where t refers to the year of the quarter preceding the merger announcement—which we refer to as the merger year for brevity. Without loss of generality, we label the two institutional investors involved in a generic merger event $m \in \mathbf{M}_t$ as A and B . The treatment set $\mathbf{T}$ is the set of firm-year tuples (f, t) for which there exists a merger $m \in \mathbf{M}_t$ between investors A and B such that the following three criteria are satisfied:

1. Investor A holds at least 1% of the outstanding shares of firm f prior to the merger.
2. Investor B holds at least 1% of the outstanding shares of some other firm j prior to the merger.
3. Neither A nor B holds *more* than 1% in *both* firms f and j before the merger.

The rationale for these criteria is to restrict the treatment set to firm-years for which merger m generates a meaningful increase in common ownership.¹³

We then partition $\mathbf{T}$ into two subsets by modifying criterion 2. We denote these subsets $\mathbf{T}_{LM}$ and $\mathbf{T}_{notLM}$, respectively. For the former, $\mathbf{T}_{LM}$, criterion 2 is replaced by the following:

- 2'. Investor B holds at least 1% of the outstanding shares of some other firm j prior to the merger, and firm j operates in *at least one* commuting zone in which the focal firm f also operates—that is, the two firms have a local labor market overlap.

¹²We checked the robustness of our results in a sample of firms from 1990 to 2006, excluding the last seven mergers in the sample provided by Lewellen and Lowry (2021), because of concerns that these mergers and firm outcomes may be contaminated by the financial crisis. However, all our results remain qualitatively unchanged.

¹³At the same time, firms satisfying these criteria are unlikely to experience significant changes in their shareholder composition or ownership concentration, since only one of the merging parties—investor A —holds more than 1% of outstanding shares, while investor B is required to hold less than 1%, or no shares at all. This distinction is important in light of Guo et al. (2024), who show that mergers between institutional investors that both hold significant stakes in the same firm tend to increase blockholder ownership, with consequent effects on firms’ innovation strategies and outcomes. The careful construction of our treatment sample, combined with our distinction between mergers affecting firms within and across commuting zones, yields differential treatment effects and allows us to conclude with confidence that changes in ownership concentration do not drive our results.

Firms in $\mathbf{T}_{LM}$ are thus those for which the merger increases common ownership with local labor-market peers, and we therefore expect their $Cindex_{LM}$, as defined above, to rise. Our first discrete treatment variable, $Treat_{LM}$, takes the value one in the year of the quarter immediately preceding the merger announcement for firms satisfying these three criteria with labor-market overlap, and zero otherwise.

We define the subset $\mathbf{T}_{notLM}$ as the complement of $\mathbf{T}_{LM}$ so the two subsets partition $\mathbf{T}$: $\mathbf{T}_{notLM} = \mathbf{T} \setminus \mathbf{T}_{LM}$. Firms in $\mathbf{T}_{notLM}$ experience an increase in common ownership with firms outside their local labor markets, and we therefore expect their $Cindex_{notLM}$ also to rise. Our second discrete treatment variable, $Treat_{notLM}$, takes the value one for firm-years belonging to $\mathbf{T}_{notLM}$ and zero otherwise.

Since the degree of treatment varies across firms depending on the pre-merger ownership stakes of the merging parties, we also construct a continuous treatment variable that exploits variation in treatment intensity *within* each treatment set. This variable is based on the implied change in the firm-pair-level $Cindex_{fjt}$ between the focal firm f and each relevant peer firm j . We define the pairwise $Cindex_{fjt}$ in year t as

$$Cindex_{fjt} = \sum_i \beta_{if} \beta_{ij}, \quad (11)$$

where ownership shares are measured as of year t . For a generic merger $m \in \mathbf{M}_t$, we compute the *implied* pairwise $Cindex$ between firms f and j as

$$\widehat{Cindex_{fj}^m} = (\beta_{Af} + \beta_{Bf})(\beta_{Aj} + \beta_{Bj}) + \sum_{i \notin \{A,B\}} \beta_{if} \beta_{ij}, \quad (12)$$

treating investors A and B as if they had already merged as of time t .¹⁴ The implied change in the firm-pair-level $Cindex_{fjt}$ due to merger m is then

$$\Delta_{fj}^m \equiv \widehat{Cindex_{fj}^m} - Cindex_{fj} = \beta_{Af} \beta_{Bj} + \beta_{Bf} \beta_{Aj}. \quad (13)$$

Next, we define the set $\mathbf{T}^{f,m}$ as the collection of firms j that, given the focal firm f and the merger $m \in \mathbf{M}_t$, satisfy the following three criteria:

1. Investor A holds at least 1% of the outstanding shares of firm f before the merger.
2. Investor B holds at least 1% of the outstanding shares of firm j before the merger.
3. Neither A nor B holds *more* than 1% in *both* firms f and j before the merger.

¹⁴Recall that year t is the year of the quarter *before* the merger *announcement*.

We partition $\mathbf{T}^{f,m}$ into two disjoint subsets. For each firm f and merger m , let $\mathbf{T}_{LM}^{f,m}$ denote the set of peer firms j in $\mathbf{T}^{f,m}$ that operate in at least one commuting zone in which f also operates, and let $\mathbf{T}_{notLM}^{f,m} = \mathbf{T}^{f,m} \setminus \mathbf{T}_{LM}^{f,m}$ denote the set of peer firms in $\mathbf{T}^{f,m}$ that do not overlap with f in any commuting zone. For firm-years in $\mathbf{T}_{LM}$, the continuous treatment captures only the implied increase in common ownership arising from merger-peer pairs with local labor market overlap.

We can now define the continuous treatment variables as follows:

$$ContTreatLM_{ft} = \begin{cases} \sum_{m \in \mathbf{M}_t} \sum_{j \in \mathbf{T}_{LM}^{f,m}} \Delta_{fj}^m & \text{if } (f, t) \in \mathbf{T}_{LM}, \\ 0 & \text{otherwise,} \end{cases} \quad (14)$$

$$ContTreatnotLM_{ft} = \begin{cases} \sum_{m \in \mathbf{M}_t} \sum_{j \in \mathbf{T}_{notLM}^{f,m}} \Delta_{fj}^m & \text{if } (f, t) \in \mathbf{T}_{notLM}, \\ 0 & \text{otherwise.} \end{cases} \quad (15)$$

In sum, for each firm-year observation, the continuous treatment aggregates the implied pairwise increases in common ownership across all relevant peer firms and all contemporaneous mergers. In the main analysis, we rely on the continuous treatment variables; robustness checks using the discrete treatment indicators yield qualitatively consistent results.

3.2.6 Control variables

We control for a significant set of control variables that could influence firms' innovation and automation decisions. Institutional ownership has been shown to influence innovation due to monitoring of managers (Aghion, Van Reenen, and Zingales, 2013; Guo et al., 2024). Since common ownership and firms' institutional ownership are related but different phenomena, we control for *InstOwn*, the percentage ownership of all institutional (13F) investors of a firm as of the calendar year-end, to disentangle both effects.

We also control for *FirmSize*, which is the natural logarithm of total assets; *R&DtoAssets*, which corresponds to R&D expenses scaled by total assets; *FirmAge*, or the natural logarithm of the number of years the firm has existed, according to Compustat. *PPEtoAssets* is firms' property, plant, and equipment scaled by total assets. We include a set of firm-level investment, valuation, or production characteristics by controlling for *LogSales*; *TobinsQ*; *MarketCap* defined as the stock price multiplied by shares outstanding; *CAPEXAssets* defined as the ratio of capital expenditures to total assets and *CapitalIntensity* defined as the ratio of production costs to sales. We also control for *Cash* and *Profitability*, calculated as operating income before depreciation divided by the book value of common equity.

3.3 Sample and Descriptive Statistics

We combine the information from the different data sources into a firm-level panel. We start with an unbalanced sample of 8,813 unique Compustat firm identifiers and 75,402 firm-year observations. We use this large sample of firms, their pairwise ownership information, and the locations of their establishments to construct our treatment and common ownership variables. Thus, we use a comprehensive sample to include all potential LM rivals and other portfolio firms operating in distinct labor markets to measure their common ownership with the focal firms.

Since our main outcome variables are constructed using patent information, we restrict the set of focal firms in the panel to estimate the effects of an increase in common ownership to those for which we observe a positive number of patents in at least one year during our sample period in the patent data provided by [Arora et al. \(2021\)](#). The final result of our sample selection process yields an unbalanced panel of 1,923 firms, comprising 19,393 firm-year observations for which none of the variables used in our analysis is missing.

Table 4 reports summary statistics for our sample. The average common ownership within labor markets is larger than the average across labor markets, with values of 0.003 and 0.002, respectively. This shows that the average firm has a slightly greater overlap of institutional shareholders with the average firm that operates in the same commuting zones than with the average firm operating in a dis-joint set of local labor markets. Paired and unpaired *t*-tests reveal that the difference is significant at 1%. Institutional investors hold 43% of the outstanding shares of the average firm in our sample, similar to findings from other studies for a similar sample period.¹⁵

Moreover, the average firm in our sample invests 13.9% of total assets into research and development (R&D) activities.¹⁶ Firms' total assets are around \$2.0B, and they are older than 16 years on average. The mean number of Employees is 5.6 thousand. Firms' ratio of tangible to total assets (*PPEtoAssets*) is 18.2%.

On average, firms produce around 21 patents per year of which 12 are classified as automation patents by [Mann and Püttmann \(2021\)](#). However, this number hides heterogeneity across firms, since the average firm's probability to produce at least one automation patent in a year is only 43.1%.

Finally, 5.8% of firm-years belong to the set $\mathbf{T}_{\text{LM}}$ and 2.2% to its counterpart $\mathbf{T}_{\text{notLM}}$. The average treatment dose for the average firm in all years (including zeros) is around 0.001

¹⁵For example, [Guo et al. \(2019\)](#) report an ownership share of 44% belonging to institutional investors in the same years for a different sample of firms.

¹⁶It is well known that some firms do not report R&D expenditures in Compustat. We do not replace them with zeros since this could potentially introduce errors.

Table 4
DESCRIPTIVE STATISTICS

Variable	25th Perc.	Median	Mean	75th Perc.	Std. Dev.	N. of obs.
Ownership:						
<i>CIndexLM</i>	0.001	0.002	0.003	0.004	0.003	19393
<i>CIndexNotLM</i>	0.001	0.001	0.002	0.003	0.002	19393
<i>InstOwn</i>	0.158	0.401	0.429	0.682	0.298	19393
Firm Characteristics:						
<i>R&DtoAssets</i>	0.026	0.079	0.139	0.163	0.226	19393
<i>TotalAssets (in \$1M)</i>	35.072	123.174	2012.929	562.663	10642.655	19393
<i>FirmAge (in years)</i>	7.000	12.000	16.368	21.000	13.179	19393
<i>Sales (in \$1M)</i>	23.060	96.132	1679.863	494.954	8392.973	19393
<i>PPEtoAssets</i>	0.068	0.141	0.182	0.253	0.151	19393
<i>Leverage Value</i>	0.001	0.083	0.164	0.251	0.331	19393
<i>Profitability</i>	-0.124	0.147	0.276	0.312	33.923	19393
<i>Cash</i>	0.065	0.229	0.302	0.485	0.268	19393
<i>Capital Expenditures</i>	0.017	0.033	0.047	0.061	0.049	19393
<i>Capital Intensity</i>	0.152	0.301	0.713	0.575	7.347	19393
<i>Tobin's Q</i>	1.259	1.858	2.822	3.128	3.748	19393
<i>Market Capitalization</i>	52.849	194.013	3034.134	825.343	16448.768	19393
<i>Employees</i>	144.000	476.000	5621.562	2350.000	22053.087	19217
<i>EmpGrowth</i>	-0.056	0.041	0.137	0.180	1.217	18169
Patent output:						
<i>NumPatents</i>	0.000	1.000	20.648	7.000	103.428	19393
<i>NumAutoPatents</i>	0.000	0.000	12.050	3.000	77.857	19393
<i>AutoDummy</i>	0.000	0.000	0.431	1.000	0.495	19393

Notes: This table presents descriptive statistics for our sample of patenting firms from 1990 to 2012. LM denotes *labor market*. R&D, Leverage Value (book debt), Cash, Property, Plant, and Equipment (PPE), and Capital Expenditures are scaled by total assets. Profitability is operating income before depreciation divided by common equity. Market capitalization is calculated as the firm's share price multiplied by the number of common shares outstanding. Tobin's Q is calculated as the market value of equity plus the book value of total assets, minus the book value of common equity and deferred taxes, all divided by total assets.

for both, *ContTreatLM* and *ContTreatnotLM*.

The set **T** of firm-years that we define as treated by a merger (as described in Section

Table 5
TREATMENT DOSE ACROSS AND WITHIN LABOR MARKETS

Set of firms:	$\mathbf{T}_{\text{LM}}$			$\mathbf{T}_{\text{notLM}}$			Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(1) - (4)
Variable	<i>Mean</i>	<i>Std. Dev.</i>	<i>N. of obs.</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>N. of obs.</i>	
<i>Treat (discr.)</i>	1.000	0.000	764	1.000	0.000	267	0.000
<i>ContTreat (cont.)</i>	0.022	0.002	764	0.025	0.001	267	-0.004

Notes: This table reports the average dose of treatment for treated firms and compares them across the two samples of treated firms, i.e., firm year in the sets $\mathbf{T}_{\text{LM}}$ (columns (1)-(3)) and $\mathbf{T}_{\text{notLM}}$ (columns (4)-(6)) as defined in this section. The t-score on the difference is -1.3042 , indicating a non-significant difference at conventional levels.

3.2.5) consists of 1,473 firm-years corresponding to 900 firms. Of these firm-years 1,035 are in the set $\mathbf{T}_{\text{LM}}$, comprising 629 unique corporations that were affected by a merger of institutional investors that likely increases their common ownership with local labor market rivals. For a firm-year to be in the set $\mathbf{T}_{\text{notLM}}$, we require that a firm in a particular year is affected by a merger, but that this event is not likely to increase common ownership with natural rivals in the labor market. Due to this restriction, we identify 438 firm-years in this set, consisting of 415 companies.

Our entire sample consists of four types of firms: (i) firms that are never treated (i.e., firms for which none of their firm-year observations is in set $\mathbf{T}$), (ii) firms that are affected only by our within labor-market treatment (i.e., firms for which at least one year appears in set $\mathbf{T}_{\text{LM}}$, but never in set $\mathbf{T}_{\text{notLM}}$), (iii) firms that are affected only by our across labor-market treatment (i.e., firms for which at least one year appears in set $\mathbf{T}_{\text{notLM}}$, but never in set $\mathbf{T}_{\text{LM}}$), and (iv) firms that are treated by both types of treatment (although in different years, i.e., those firms for which at least one year appears in set $\mathbf{T}_{\text{LM}}$ and at least one other year appears in $\mathbf{T}_{\text{notLM}}$).

In pooled regressions in the Appendix (Section D) we use all 1,035 event firm-years to estimate the effect of *ContTreatLM* in a robustness check. However, in order to provide clean estimates for both treatments and avoid potential contamination, in our baseline estimation, we exclude observations of firms that are treated at least once during our sample period by the treatment *ContTreatnotLM*, when estimating the effect of *ContTreatLM*, i.e., to estimate our within labor-market effect we only use firms in (i) and (ii). This leaves us with a sample of 764 observations in $\mathbf{T}_{\text{LM}}$. To estimate the effect of *ContTreatnotLM* we proceed analogously (excluding all observations of firms that are treated at least once by *ContTreatLM*), i.e., using only firms in groups (i) and (iii). This results in 267 observations in the set $\mathbf{T}_{\text{notLM}}$.

Next, we compare the average treatment doses among the two sets of treated firm-years

in Table 5. That is, we compare the mean treatment doses within each treatment sample across the two subsets of firms affected by mergers. In the treatment group $\mathbf{T}_{\mathbf{LM}}$, the average treatment dose of the 764 firm-year observations is 0.022. To help understand this number, simple calculations reveal that the average treatment dose of 0.022 corresponds, for example, to the focal firm having a 5% blockholder (say, investor A) that merges with another institutional investor (say, B). In the symmetric case, this other investor holds 5% in roughly 8 firms in which A is not invested, and these firms are active in a subset of commuting zones where the focal firm operates.

The average treatment dose for the 267 firms in the set $\mathbf{T}_{\mathbf{notLM}}$ is almost 20% higher, at 0.025.¹⁷ In all our DID estimations, we report point estimates representing the economic effects of a treatment dose for the average event firm in the respective sample to facilitate interpretation and comparison.

3.4 Identification strategy

We now describe in detail our identification strategy. The causal object of interest is the effect of exogenous changes in common ownership on firms’ automation strategies. A key feature of this setting is that firms may experience changes in common ownership at different points in time and potentially multiple times over the sample period. Moreover, changes in ownership are unlikely to affect innovation outcomes contemporaneously, given lags between investment decisions and the realization of patentable technologies.

In such environments, conventional two-way fixed effects models with leads and lags can yield biased estimates and misleading pre-trend diagnostics when treatment effects are heterogeneous and dynamic. As shown by [Sun and Abraham \(2021\)](#), dynamic coefficients in TWFE models can be expressed as weighted averages of cohort-specific effects across time, which makes it difficult to disentangle short-run responses from longer-term changes in firms’ strategic orientation. In our context, this implies that standard TWFE regressions cannot separately identify the immediate impact of changes in common ownership from persistent shifts in firms’ innovation strategies.

To address these concerns, we employ the event-study difference-in-differences framework developed by [De Chaisemartin and d’Haultfoeuille \(2024\)](#). This approach allows us to accommodate staggered treatment timing, continuous treatments, and multiple treatment events, under a set of more transparent and credible identifying assumptions. For each model we estimate an average treatment effect (ATT), as well as a set of six dynamic post-treatment

¹⁷This average treatment dose corresponds to the merger of a 5% blockholder of the focal firm with an investor that holds 5% of 10 firms without labor-market overlap to the focal firm in which the other one is not invested before the merger.

effects. Each dynamic effect measures a level difference between treatment and controls at each respective post-treatment period. In other words, each coefficient captures a snapshot of how much higher or lower the outcome is, on average, than it would have been had the firm not been treated. While each dynamic effect aggregates across many firms and treatment events, it conditions on the time since treatment and thus represents a cross-sectional average at a fixed post-treatment horizon.

The ATT aggregates these level differences across groups, treatment events, and post-treatment periods and then normalises by total treatment exposure. Since we use a continuous treatment model, we multiply the ATT by the average treatment dose and re-scale by 100. Therefore, the ATT should be interpreted as the total change in each outcome measure given the average treatment dose. The dynamic effects allow us to examine the shape of any treatment effect found. For example, does the outcome increase quickly but then subsequently the treatment effects fade? Or is there a time delay before the treatment effects appear? In addition, we estimate a set of 3 placebo pre-treatment coefficients, which allow us to compare the treated group to the control before a treatment event. They allow us to assess the plausibility of parallel trends in the pre-treatment period (i.e., the placebo coefficients are jointly not statistically different from zero at conventional significance levels) and to test for anticipation effects (that is, any statistically significant placebo prior to treatment).

We exploit mergers between institutional investors as plausibly exogenous shocks to common ownership across firms. The identifying assumption underlying our difference-in-differences design is that, absent investor mergers, treated and control firms would have experienced similar changes in automation outcomes. Identification would be threatened only if the timing of institutional mergers were correlated with anticipated changes in firms' automation strategies that would have occurred even in the absence of the merger. Selection based on static firm characteristics, including average automation intensity, therefore does not invalidate the design. This strategy was popularized by [He and Huang \(2017\)](#). They argue that mergers among institutional investors are largely driven by broader forces including consolidation in the asset management and banking sectors, rather than expectations about the future behavior of specific portfolio firms.

Our empirical results provide further support for this identifying assumption. We distinguish between cases where mergers increase common ownership among firms that overlap in labor markets and cases where firms do not share labor markets. We find increases in automation patenting only when firms overlap in labor markets, and no increase when they do not. If investor mergers were systematically timed to anticipated increases in automation innovation that would have occurred even in the absence of the merger, we would expect to

observe increases in automation patenting in both cases. The absence of effects when labor markets do not overlap is therefore inconsistent with such an anticipation story and instead supports the mechanism proposed in this paper, whereby increases in common ownership affect automation incentives only when firms compete for workers in the same local labor markets.

Having established the validity of our common-ownership shock, we now describe the empirical strategy used to test our hypotheses. To evaluate Hypothesis 2.2, we focus on changes in a firm’s common ownership with respect to its local labor-market (LM) rivals. Accordingly, we employ the continuous treatment variable *ContTreatLM*, which captures exogenous changes in common ownership with LM rivals induced by institutional-investor mergers. Our primary outcomes of interest are firms’ automation strategies, measured using *AutoRatio* and *AutoDummy*. All regressions control for the firm-level characteristics described in Section 3.2.6.

Next, we examine our alternative Hypothesis 2.2, which examines the effects of increasing common ownership with firms that do not share a local labor market with the focal firm. We apply our continuous treatment variable *ContTreatnotLM*, analogously. Thus, we test whether a firm that experiences a positive shock to common ownership only with firms with which it does not compete for labor increases the automation content of its innovation output.

As mentioned, the DID method we apply accounts for the fact that firms are treated several times. However, it does not account for firms being treated by other events. Because we expect that the two treatments (increases in common ownership with regard to labor market rivals and non-rivals) are different, we remove firms contaminated by separate treatment merger events. We remove potential control and treatment firms that are ever treated by a merger event that exclusively treats common ownership across labor markets. To be precise, when estimating the effect of *ContTreatLM*, we exclude all companies from the sample for which there is any firm year in which *ContTreatnotLM* takes a positive value, and vice versa. For robustness, we have also estimated the effects in pooled samples, which are included in Appendix Section D. All our main results are robust to the choices regarding sample selection.

One potential criticism of our identification method comes from the critique raised in [Lewellen and Lowry \(2021\)](#) that these mergers are bunched over time. For instance, there were a large number of mergers around the financial crisis. If other, automation-relevant events occurred at the same time, e.g., firms increase automation to alleviate competitive pressure during the financial crisis, then our coefficients may be biased. To combat this issue, we have also run the model on data before the onset of the crisis in 2007. All our results

stay qualitatively consistent with our baseline analysis, therefore reducing this concern. We report the results in the appendix (Section D). We have also estimated our model using the discrete treatment variables (*TreatLM* and *TreatnotLM*) and report results (Section D in the appendix) that are consistent with our estimations using continuous treatments.

3.5 Empirical Results

In this section, we present the results of the dynamic Difference-in-Differences model, using an identification strategy based on institutional mergers.¹⁸

3.5.1 Common Ownership of Labor Market Rivals and Automation Innovation

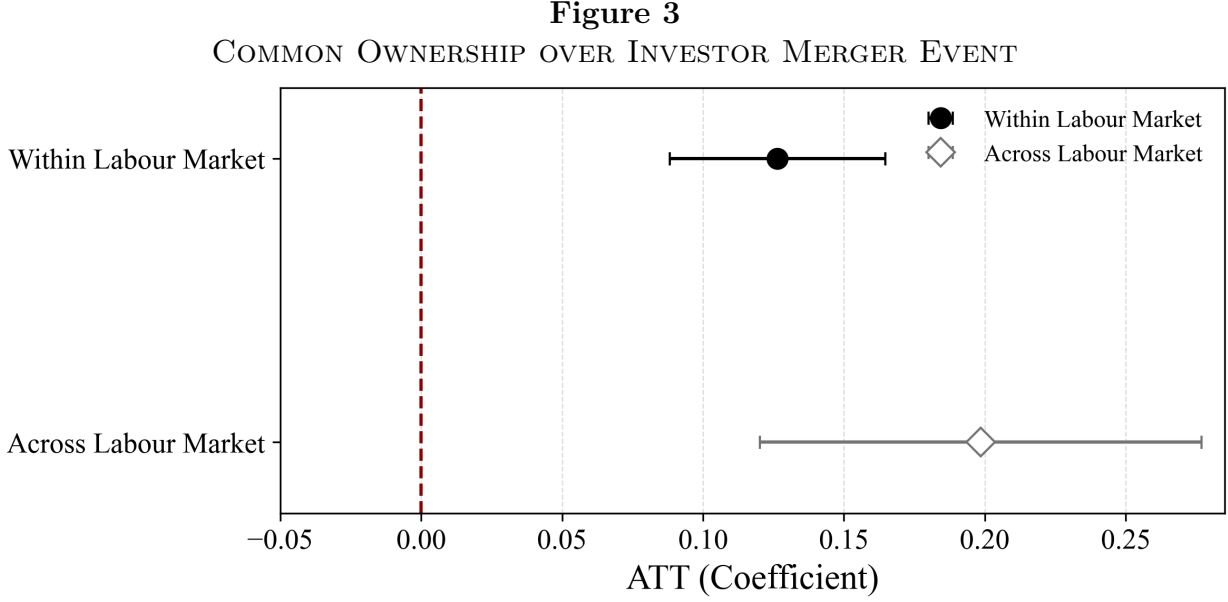
Relevance of Treatment—In Figure 3, we show that mergers between institutional investors lead to an increase in average common ownership, using continuous treatments for both within-labor-market (*ContTreatLM*) and across-labor-market (*ContTreatNotLM*) changes in common ownership. *CindexLM* is used as the dependent variable for firms that likely experience an increase in common ownership with firms in the same commuting zones (within labor markets). In contrast, we use *CindexNotLM* as the outcome variable for the treatment across labor markets. Lewellen and Lowry (2021) show that institutional mergers lead to an increase of common ownership on the firm-pair level. Figure 3 shows that, for both treatments, affected firms experience a higher level of common ownership relative to the pre-treatment baseline.

Common ownership increases by 0.126 percentage points following a within-labor-market institutional investor merger. This corresponds to 0.42 standard deviations of *CindexLM*.¹⁹ Regarding the across labor-market institutional investor merger events, the ATT is slightly higher, at 0.199, corresponding to almost one standard deviation in *CindexNotLM*. This is consistent with the fact that the average treatment dose of *ContTreatNotLM* is also larger than *ContTreatLM* as shown in Table 5.

One concern may be that after merging, the merging institutional investors or other institutions adjust their portfolios such that the effect on common ownership could be negligible or disappear quickly. Also, it is crucial in our setup that an increase in common ownership with a labor market rival on the firm-pair level is not compensated by other changes in common ownership with other firms, given that our outcome variables are defined on the

¹⁸In Appendix B we present an OLS model and show estimates of the association between labor-market common ownership and automation in Table 6.

¹⁹All coefficients are calculated by multiplying the estimated ATT from a unit change in the treatment variable scaled by the average treatment dose, and then converted into percentage points by multiplying by 100. That is the coefficients show the change in common ownership of the average treated firm in percentage points.



Notes: This figure reports the average total effect of being treated by an institutional merger that likely increases common ownership with LM rivals (*ContTreatLM*) on the raw firm-level common ownership regarding LM rivals (*CindexLM*, upper estimate) and the corresponding effect on common ownership across LM (*CindexNotLM*, bottom estimate) of the alternative treatment (*ContTreatNotLM*). The estimation model is outlined in [De Chaisemartin and d’Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6. The full dynamic model coefficients are given in Appendix section C.

firm level. The dynamic effects are reported in Figure 11 in the Appendix. The figure shows that common ownership remains elevated for treated firms, compared to the pre-treatment baseline, up to six (within LM) and four (across LM) years after the shock.

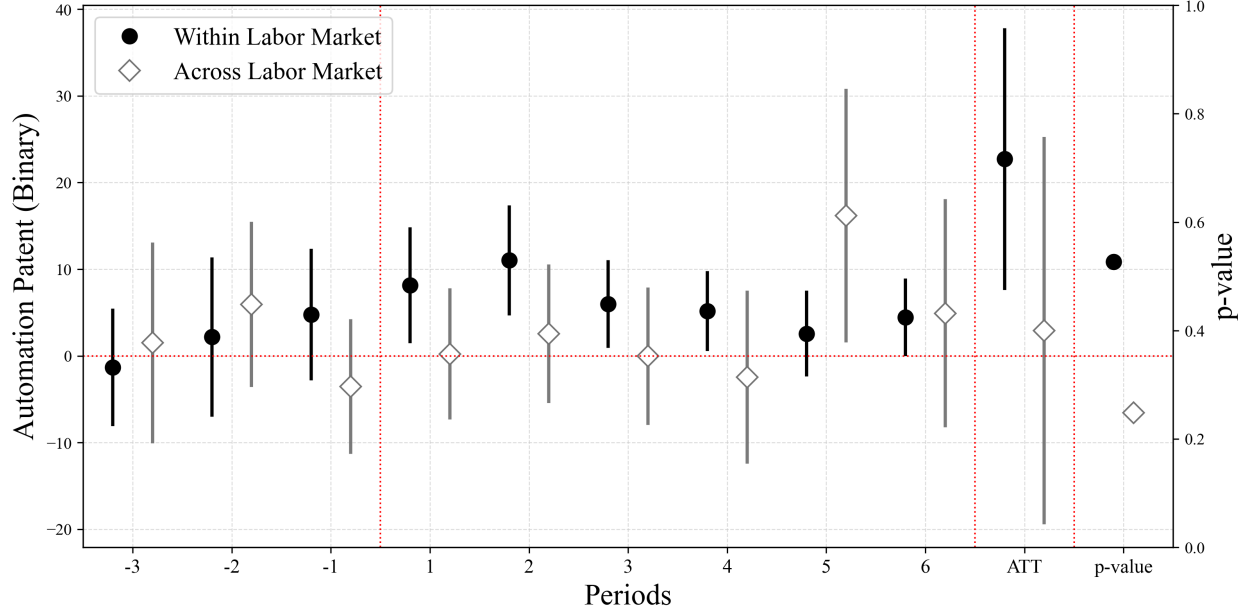
Automation Strategy—We begin by testing Hypothesis 2.2 using the binary outcome *AutoDummy*, which equals one if the firm produces at least one automation patent in a given year. This specification allows us to examine whether firms adjust their innovation strategy by increasing their propensity to develop automation technologies.²⁰

Figure 4 reports the estimated dynamic treatment effects and the average total treatment effect (ATT) for both the within- and across-labor-market treatment models. Consistent with the labor-market mechanism derived from the theoretical model, we find that increases in common ownership with local labor-market rivals significantly raise the probability that treated firms in $\mathbf{T}_{LM}$ produce an automation patent. The estimated ATT corresponds to a 22.7 percentage-point increase in the annual probability of automation patenting for the average treated firm.²¹ Given a baseline annual probability of automation patenting of 0.431,

²⁰We also examine continuous automation measures, such as *AutoRatio*, to test whether exogenous changes in common ownership affect firms’ automation activity on the intensive margin. These results are presented in the appendix and summarized in Figure 6.

²¹The estimated ATT equals 10.324. Evaluated at the average treatment dose of 0.022, the implied effect is $10.324 \times 0.022 \approx 0.227$, corresponding to a 22.7 percentage-point increase after scaling coefficients by 100.

Figure 4
AUTOMATION RESULTS: BINARY MODEL



Notes: A figure plotting the dynamic effects and average total treatment (ATT) effects for the treatment model with a binary outcome equal to one if that firm applied for an eventually granted automation patent in that year (*AutoDummy*) for the within (*ContTreatLM*) and across (*ContTreatNotLM*) labor market treatments, respectively. The estimation model is outlined in [De Chaisemartin and d’Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6. The p-value tests the null hypothesis that all of the three placebo effects prior to the treatment are equal to zero.

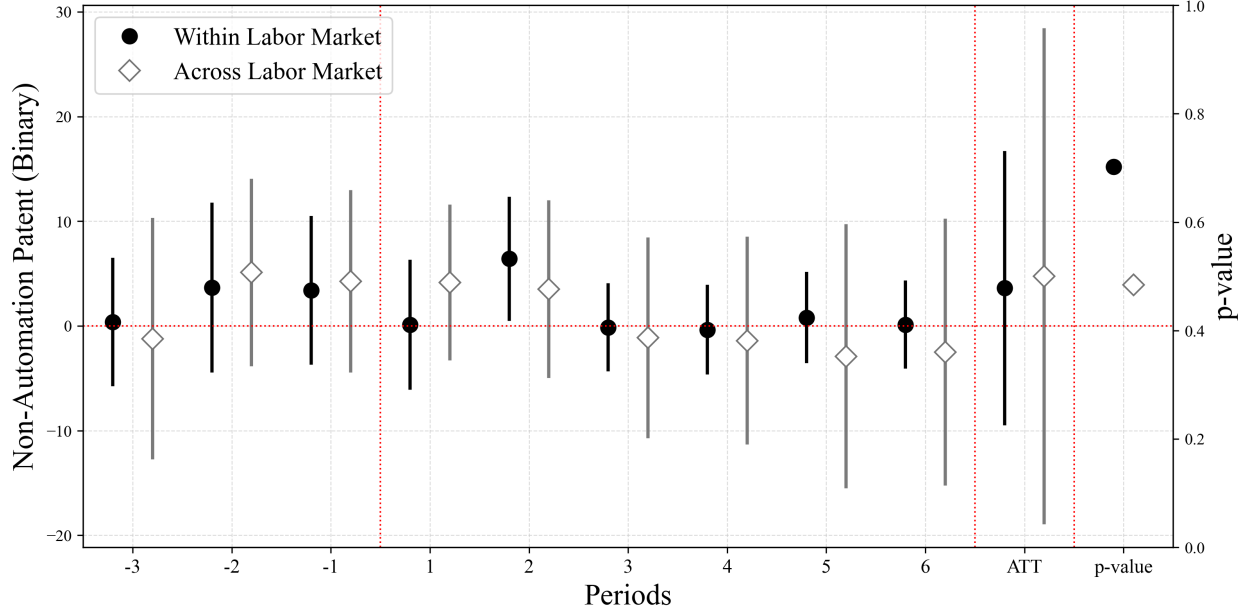
this implies an increase of roughly $0.227/0.431 \approx 53\%$ relative to the baseline probability.

On the contrary, we do not observe a significant change in the average automation propensity when common ownership increases across local labor markets, i.e., for firms in $\mathbf{T}_{\text{notLM}}$. Across the six post-treatment horizons, only one coefficient is statistically significant. Consistent with this pattern, the ATT is close to zero and statistically insignificant. In other words, common ownership appears to spur automation only when the local labor-market channel is active. This provides the first empirical support for the mechanism derived in the theoretical model. Figure 5 complements these results by showing that there is no corresponding increase in the propensity to produce non-automation patents.²²

Overall, our results suggest that increases in common ownership among firms competing for workers increase their automation innovation output. Importantly, we have provided strong evidence that the effect of common ownership is realized only when it occurs between

²²Figure 12 in the appendix shows this directly by replacing the outcome with a binary indicator for whether the firm produces any patent in a given year. While firms treated by a within-labor-market shock exhibit a significant increase in patenting activity, this effect again disappears when common ownership changes occur across labor markets.

Figure 5
NON-AUTOMATION RESULTS: BINARY MODEL

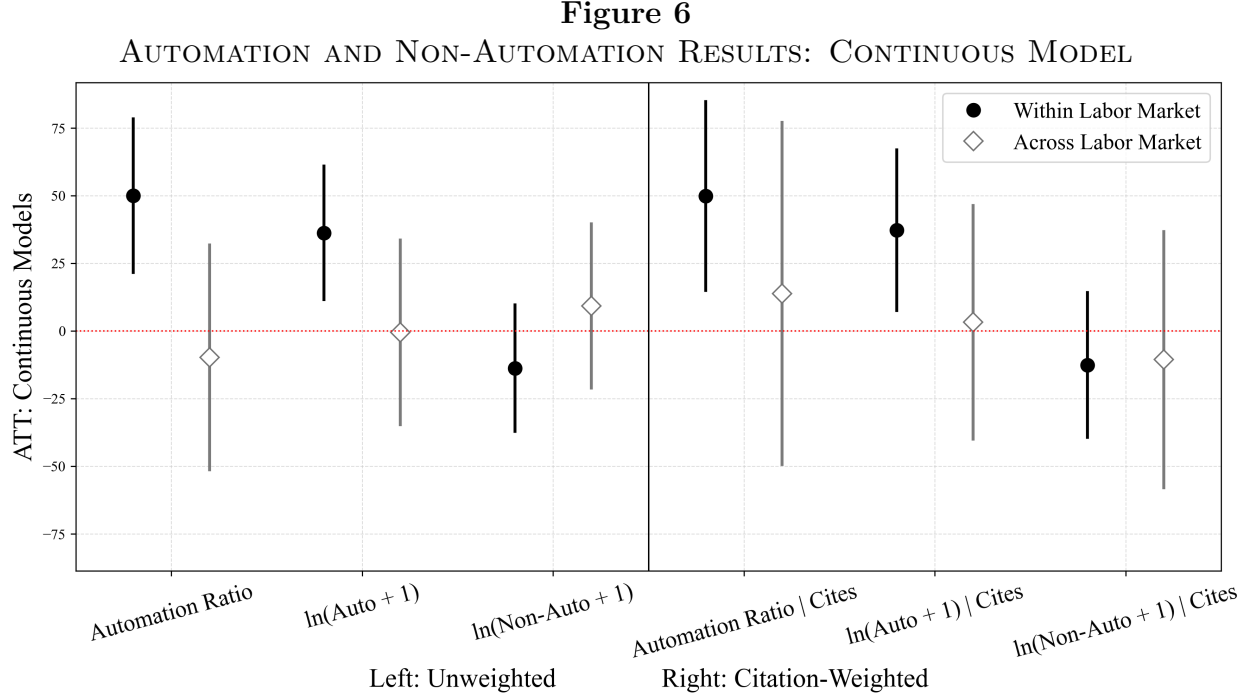


Notes: A figure plotting the dynamic effects and average total treatment (ATT) effects for the treatment model with a binary outcome equal to one if that firm applied for an eventually granted non-automation patent in that year for the within (*ContTreatLM*) and across (*ContTreatNotLM*) labor market treatments, respectively. The estimation model is outlined in [De Chaisemartin and d’Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6. The p-value tests the null hypothesis that all three placebo effects before the treatment are equal to zero.

firms that share a labor market.

To assess effects on the intensive margin, we use patent counts and control for patent quality using citation counts. The results are shown in Figure 6. In both panels, the ratio of automation to non-automation innovation increases with greater common ownership within labor markets. Consistently, the number of automation patents and the number of citations they receive increase for treated firms. This indicates that the within-labor-market treatment causes firms to produce more automation patents, but there is no simultaneous reduction in patent quality.

To put the size of the effect in economic terms, we start from the estimated Average Total Effect (ATT) of our dynamic difference-in-differences model. The ATT for *lnAuto* is 36.23 (where all coefficients are scaled by 100). Dividing by 100, the estimate implies that the average investor merger multiplies a treated firm’s $(1 + \text{AutomationPatents})$ by $\exp(0.3623) \approx 1.44$ over the six years following the event. Because the dependent variable is $\ln(1 + Y)$ rather than $\ln(Y)$, where Y is the number of automation patents, this 44 percent increase applies to $(1 + Y)$, and the implied percentage change in the patent count Y itself



Notes: A figure plotting the average total treatment (ATT) effects for the treatment models within (*ContTreatLM*) and across (*ContTreatNotLM*) labor markets on different continuous patent output variables. Automation Ratio (Automation Ratio | Cites) is the natural logarithm of the quotient of (one plus) the number of automation patents (cites) to the number of (one plus) the number of non-automation patents (cites, respectively). Additional outcome variables are the natural logarithm of (one plus) the number of automation or non-automation patents (cites, respectively). All measures using cite counts adjust cite numbers for each patent by the average number of cites in the same application year and technology class. The estimation model is outlined in [De Chaisemartin and d’Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

depends on the firm’s baseline level of patenting.

To illustrate this, we evaluate the effect at several points of the highly right-skewed patent distribution reported in Table 4. The median firm in our sample produces zero automation patents per year. For such a firm, the treatment would raise $(1 + Y)$ from 1 to 1.44, implying an increase of less than one additional automation patent per year—consistent with the large estimated effect on the extensive margin (the 22.7 percentage-point increase in *AutoDummy*). At the 75th percentile, where firms produce 3 automation patents per year, the treatment raises $(1 + 3) = 4$ to $4 \times 1.44 = 5.75$, implying an increase from 3 to about 4.75 patents, or roughly 1.75 additional automation patents per year (a 58 percent increase in Y). At the sample mean of 12.05 patents per year, where $(1 + Y) = 13.05$, the treatment implies $13.05 \times 1.44 \approx 18.75$, or about 5.70 additional automation patents per year (a 47 percent increase). Over a six-year window, this corresponds to roughly 34 additional patents relative to a baseline of 72.

These calculations highlight that the absolute patent-count gains are concentrated among

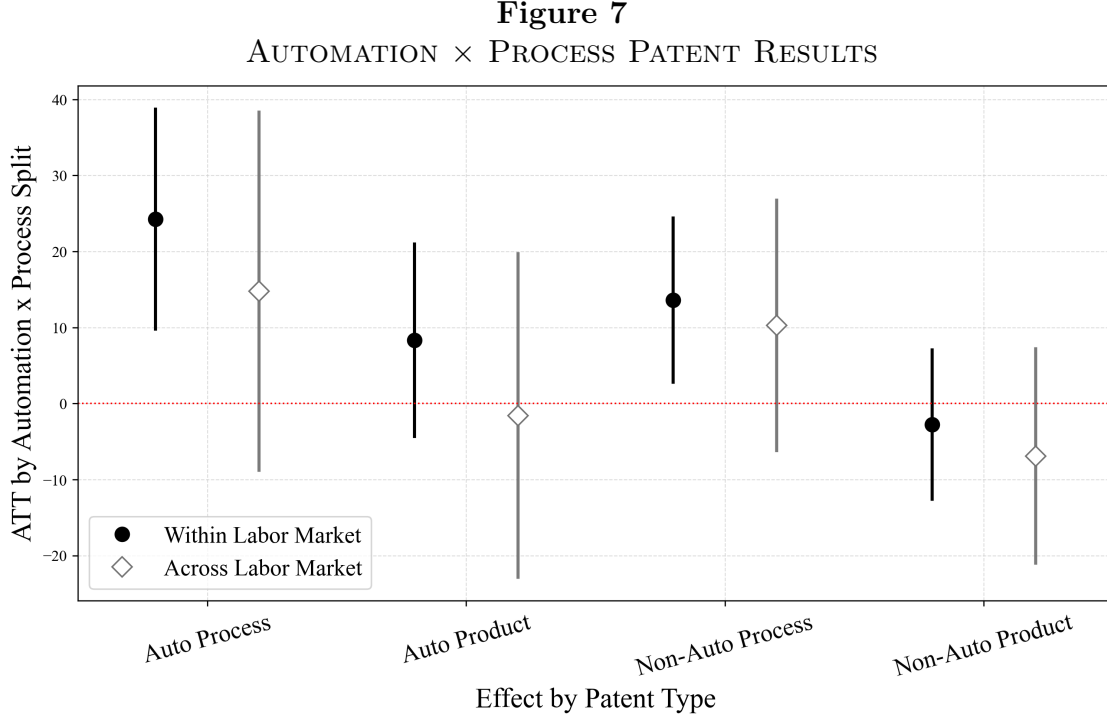
firms that are already active in automation patenting. For most firms in the sample, the primary margin of adjustment is the extensive one: moving from zero to positive automation output. Because this estimate comes directly from the ATT without any extrapolation beyond the observed treatment dose, we treat the 44 percent increase as the paper’s primary measure of economic magnitude.

How large is this relative to typical variation in common ownership? The average investor merger raises common ownership ($CindexLM$) by 0.00126 (ATT = 0.126, scaled by 100). Dividing the reduced-form effect by this first-stage effect gives $36.23/0.126 \approx 287.5$, the implied effect of a one-unit change in common ownership. Since common ownership has a cross-sectional standard deviation of 0.003 (Table 4), a one-standard-deviation increase corresponds to $287.5 \times 0.003 \approx 0.86$ log points in $lnAuto$ over six years. Converting via exponentiation, $\exp(0.86) \approx 2.37$, so $(1 + Y)$ would increase by roughly 137 percent. At the 75th percentile (3 patents per year), this implies an increase from 3 to about 8.48 patents per year (a 183 percent increase in Y); at the sample mean (12.05 per year), from about 12.05 to 29.92 patents per year (a 148 percent increase in Y), corresponding to roughly 107 additional patents over six years. However, this calculation extrapolates well beyond the observed treatment variation and rests on a linearity assumption that is unlikely to hold at larger doses of common ownership. Diminishing returns to R&D investment, capacity constraints in the innovation process, and general-equilibrium responses—such as rising costs of automation inputs or endogenous wage adjustments—would all work to attenuate the effect at higher levels. We therefore interpret this figure as an upper bound that conveys the direction and approximate order of magnitude of the relationship, rather than a literal prediction of what a large increase in common ownership would produce.

In contrast, these firms do not produce more non-automation innovation. Furthermore, firms experiencing increases in common ownership with firms outside their local labor markets do not experience significant changes in any of the innovation margins. Thus, our analysis on the intensive margin corroborates the previous results on common ownership, automation, and the labor-market channel.

3.5.2 Mapping Automation into the Firm’s Production Function

Our theoretical model predicts that firms automate their production function in response to common ownership shocks with firms in the same labor market. To show that the firms in our empirical sample are targeting automation patents predominantly towards their production functions, we use the process-product patent distinction outlined in Section 3.2.3. Our hypothesis, derived from the theoretical model in Section 2, is that common ownership incentivizes firms to produce process-automation patents, which allow them to substitute

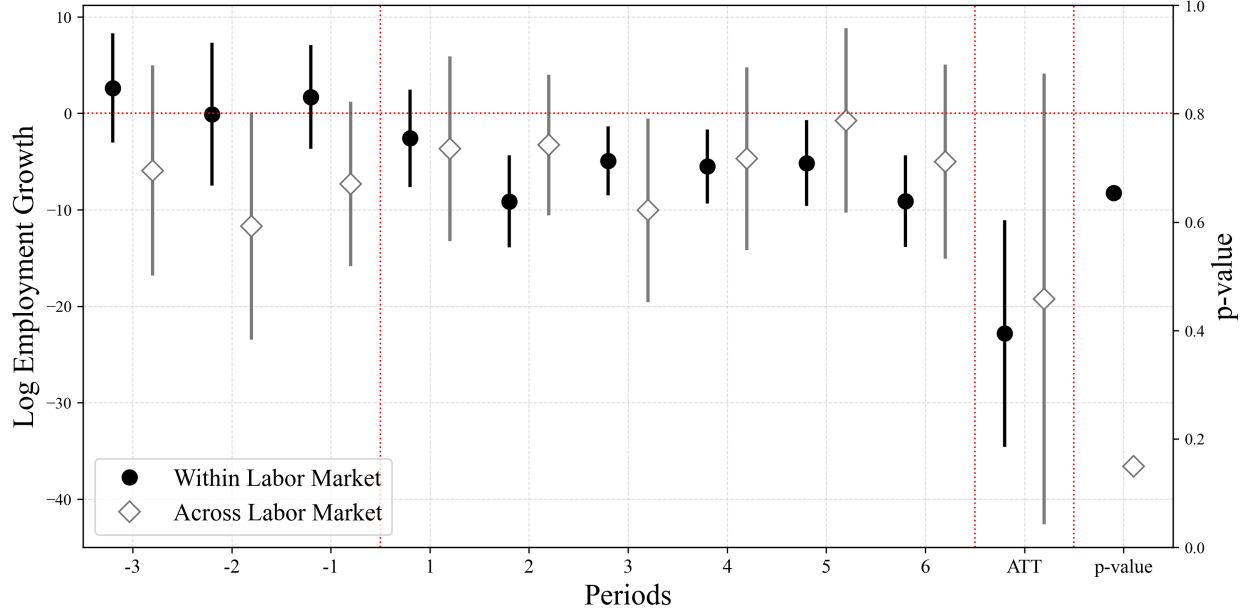


Notes: This figure plots the Average Total Treatment effects for eight models. Each estimated with the [De Chaisemartin and d’Haultfoeuille \(2024\)](#) method, the model controls for the full set of control variables listed in section 3.2.6. The outcome variable in each model is an indicator variable that takes the value one if a firm in a given year applies for an eventually granted patent in the category given on the x-axis, for each of the two models—both within (*ContTreatLM*) and across (*ContTreatNotLM*) labor market treatments. Automation patents are classified using the [Mann and Püttmann \(2021\)](#) binary classification, and process and product patents are classified using [Bena and Simintzi \(2024\)](#) classification of patent claims.

tasks from labor to capital. Product patents that are automation could include consumer products for home production, and our theoretical model suggests no reason for firms to redirect their innovation towards this group.

Figure 7 plots the average treatment effect across eight models. One for each of the process $\times$ automation classifier dummy variables, for both the within- and across-local-labor-market models. The result is striking. Increasing common ownership within local labor markets causes an increase in automation patents targeted at the production function, but does not lead to an increase in automation products. This maps closely into the propositions of the model. In cases where firms internalize their employment choices regarding wages, they target their innovation at automating tasks in the production function. Interestingly, there is also a marginally significant effect on non-automation process patents. This is also consistent with the mechanism in our model if firms react to the higher effective cost of labor by investing not only in automation technologies, but more broadly in process innovations that economize on labor by raising worker productivity.

Figure 8
EMPLOYMENT GROWTH RESULTS



Notes: A figure plotting the dynamic effects and average total treatment (ATT) effects for the treatment models using the within (*ContTreatLM*) and across (*ContTreatNotLM*) labor market treatments on log employment growth at the firm level. The estimation model is outlined in [De Chaisemartin and d’Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6. The p-value tests the null hypothesis that the placebo effects before the treatment are equal to zero.

3.5.3 The Employment Effects of Common Ownership under Labor Market Rivalry

We have shown that increases in firms’ common ownership within local labor markets affect firms’ automation strategies, leading them to automate their production processes to a greater extent. We now turn to the consequences for employment. Using our treatment *ContTreatLM* (*ContTreatNotLM*), we estimate the effect of common ownership within (across) labor markets on firms’ hiring decisions. We present our results as employment growth rates. The results are shown in Figure 8.

Again, only for our within-labor-market treatment does employment growth exhibit a significant negative effect. Reported coefficients are scaled to represent the effect of treatment evaluated at the average treatment intensity given in Table 5. The dependent variable is the annual employment growth rate, defined as the log difference in employment between year t and $t - 1$. The estimated ATT of -0.228 log points implies that, on average across post-treatment years, the treatment reduces annual log employment growth by 0.228. Because the outcome is expressed in logs, this corresponds to a multiplicative change in the employment growth factor of $\exp(-0.228) \approx 0.80$. In other words, the treatment reduces the employment

growth factor to about 80 percent of its counterfactual level.²³

The coefficient for the across-market treatment is also negative and of similar magnitude. While this pattern is consistent with the possibility that common ownership affects employment through channels other than local labor market interactions, we interpret it cautiously given the lack of statistical significance. One potential mechanism operates through product-market competition. If common ownership softens competition among rival firms, firms may have weaker incentives to expand output and invest in physical capital, which could in turn reduce labor demand.²⁴ However, only when firms experience an increase in common ownership with local labor-market rivals do we observe a statistically significant reduction in employment growth.

3.5.4 Robustness Checks

In this section, we assess the robustness of our main findings on the effect of within-local labor market (LM) changes in common ownership on firms' automation strategies. Across all robustness exercises, the qualitative conclusions from our baseline specification remain unchanged. Firms exposed to an increase in common ownership among local labor market rivals exhibit a statistically and economically significant increase in automation-related innovation, while non-automation patenting remains largely unaffected. Crucially, these effects remain absent for firms treated by cross-local labor market changes in common ownership, reinforcing our interpretation that local competitive interactions are central to the observed responses. A summary of the results is shown in Figure 9.

Discrete Treatment—First, we test the sensitivity of our results to alternative definitions of the treatment variable. Specifically, we replace the continuous measure of changes in common ownership with a discrete treatment indicator. The dynamic treatment effects associated with this specification are presented in Figure 19 in the Appendix. The results closely mirror those from the baseline analysis: within-LM increases in common ownership lead to a rise in firms' automation activity, while no comparable effects emerge for across-LM

²³To provide an economically intuitive benchmark, we evaluate this effect at the sample mean. The average log employment growth in the sample is 0.137, corresponding to an average annual growth rate of about 14.7 percent. Applying the estimated treatment effect implies a post-treatment log growth rate of $0.137 - 0.228 = -0.091$, which corresponds to an annual employment change of approximately -8.7 percent. Hence, at the sample mean, the estimate implies a shift from roughly $+15$ percent employment growth to about -9 percent, a decline of approximately 23 percentage points.

²⁴This interpretation is consistent with the common-ownership literature emphasizing that overlapping ownership can induce firms to internalize rivals' profits and compete less aggressively in product markets; see, for example, O'Brien and Salop (1999), Azar and Vives (2021), López and Vives (2019), and He and Huang (2017). In particular, López and Vives (2019) show that overlapping ownership leads to the internalization of rivals' profits and can reduce output in some settings. More broadly, Gutiérrez and Philippon (2017) link weaker competition to lower investment.

treatments or for the propensity to produce non-automation innovation.

Pooled sample—Second, we examine whether our results are driven by the sample restrictions imposed to avoid treatment contamination. In the baseline analysis, we estimate the effects of within-local labor market (LM) and across-LM changes in common ownership using different samples as outlined in section 3.3. As a robustness check, we relax this restriction and estimate pooled regressions that include all firm-years affected by mergers that increase common ownership with local labor market rivals, regardless of whether the firm is also treated by the alternative treatment at another point in time. This pooled sample comprises 1,035 treated firm-years corresponding to 629 unique firms. The resulting dynamic effects are shown in Figure 17. The estimates remain qualitatively unchanged, indicating that our baseline findings are not driven by the exclusion of firms with overlapping treatment exposure.

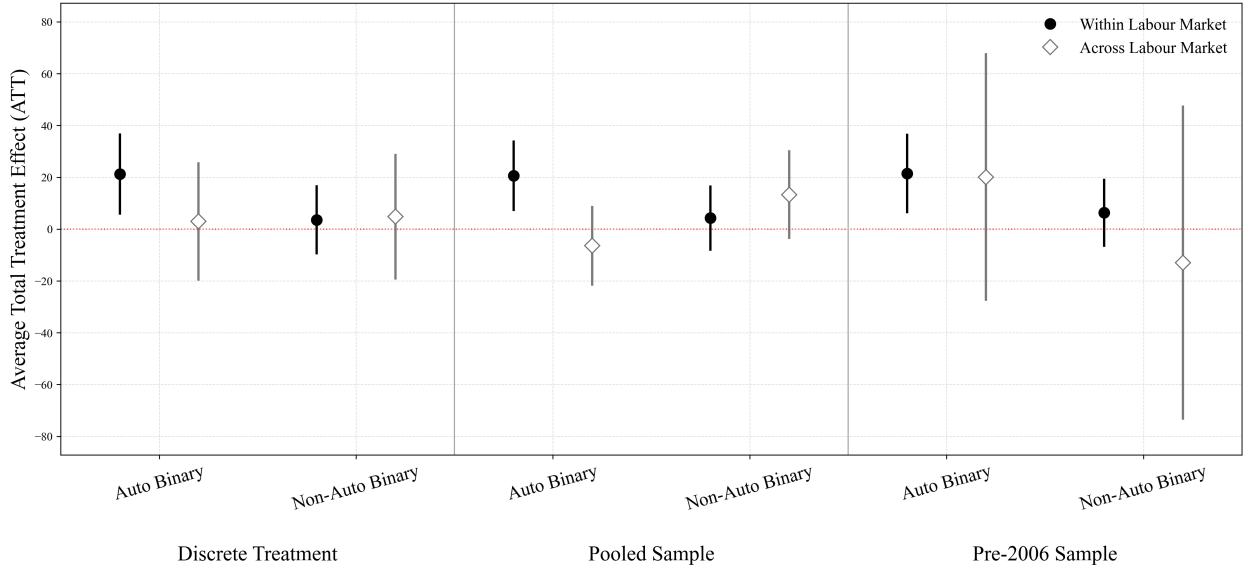
Pre-2007 Sample and Financial Crisis Concerns—Finally, we address the concern that our results may be influenced by abnormal economic conditions surrounding the global financial crisis. To this end, we replicate the baseline analysis using only data up to 2006. This restriction also implies excluding the final seven institutional mergers identified by [Lewellen and Lowry \(2021\)](#), including the BlackRock–Barclays Global Investors merger that has played a prominent role in earlier empirical studies.²⁵ The dynamic treatment effects for this subsample are reported in Figure 18.

This exercise is particularly relevant in light of [Lewellen and Lowry \(2021\)](#), who argue that the empirical relationship between common ownership and firm behavior may be sensitive to the time period studied and to the inclusion of large, crisis-era institutional mergers. By focusing on the pre-2007 period, we ensure that our results are not driven by extraordinary financial market disruptions or by a small number of high-profile mergers. Reassuringly, the estimated effects remain qualitatively unchanged: within-LM increases in common ownership continue to induce higher automation innovation, while across-LM changes do not generate significant responses.

Overall, these robustness checks confirm that our main findings are stable across alternative treatment definitions, sample constructions, and time periods, strengthening the interpretation that local labor market common ownership plays a causal role in shaping firms’ automation strategies.

²⁵See, for example, [Azar et al. \(2018\)](#).

Figure 9
ROBUSTNESS CHECK RESULTS



Notes: A figure plotting the average total treatment (ATT) effects for each of the three robustness checks. Each model is run on both the automation patent binary outcome variable and the non-automation patent binary outcome variable. The full dynamic coefficients are presented in section D. The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

4 Conclusion

We develop and test a theory of the impact of common ownership on firms' automation strategies. We show, both theoretically and empirically, that increases in common ownership of firms with local labor market rivals lead to increases in the number of automation patents and the overall automation content of the firms' innovation output. Thus, we provide evidence that institutional common ownership influences firms' innovation strategy and the direction of technological change, steering portfolio firms to focus more on automation in their innovation process. Moreover, we find no evidence that exogenous changes in common ownership between a focal firm and companies operating in distinct labor markets increase automation. This result is consistent with the mechanism we develop in our model. That is, institutional common ownership increases firms' incentives to automate to reduce labor market competition among portfolio firms. Consistent with this, we observe that increases in firms' common ownership with labor market competitors reduce firms' future employment growth.

The implications of these results are critical for policymakers concerned with the effects of technological change, especially the advancement of automation technologies, on social welfare and inequality. [Acemoglu et al. \(2020\)](#) have made the case that automation in

the United States may already be occurring excessively. Our research demonstrates that the substantial rise in common ownership, observed in both the US and Europe, further incentivizes firms to develop and implement technologies aimed at substituting human labor. Automation that stems from common ownership — rather than from genuine efficiency gains — may worsen the relationship between technological change and labor-market outcomes, depressing wages, employment, and the labor share of income, and compounding the risk of excessive automation. These considerations suggest that regulatory scrutiny of common ownership should account not only for its effects on consumer prices but for its broader influence on labor markets and the trajectory of automation.

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A Theoretical Appendix

Proof. To prove proposition 2.1, we proceed in two steps. First, we prove the proposition in a much simpler setting with two firms and a single local labor market in which they overlap. Second, we show how the result in step one is easily established in the general model.

Consider the maximization problem of firm f , which has a degree of Common Ownership with firm j , with which it also shares a local labor market,

$$\begin{aligned}
 & \max \quad p_f Y_f - r K_f - w(L) L_f + \lambda (p_j Y_j - r K_j - w(L_f + L_j) L_j) \\
 & \text{subject to} \\
 & Y_f = \exp \left(\int_0^1 \ln [y_f(x)] dx \right)^\nu \\
 & y_f(x) = \gamma_m(x) m_f(x) + \gamma_l(x) l_f(x) \\
 & K_f = \int_0^I m_f(x) dx \\
 & L_f = \int_I l_f(x) dx
 \end{aligned} \tag{16}$$

Given the assumption regarding the comparative advantage structure, the first-order conditions (FOCs) of the problem are,

$$\begin{aligned}
 [m(x)] & \implies m(x) = \frac{Y}{r} \nu \\
 [\ell(x)] & \implies \ell(x) = \frac{Y}{W} \nu \\
 [I] & \implies \frac{\gamma_\ell(I_f)}{\gamma_m(I_f)} = \frac{W}{r}
 \end{aligned} \tag{17}$$

with W being equal to the marginal cost of labor,

$$W = w(L) + w'(L)(L_f + \lambda L_j). \tag{18}$$

Rearranging the FOCs, we obtain that the solution to the firms' problem is the solution to the two-equation, two-unknowns problem. The system of equations—graphically depicted in Figure 10—is the following:

$$\begin{aligned}
 L_f &= (1 - I_f) \left(\frac{W}{r} \right)^{\frac{I_f \nu - 1}{1 - \nu}} \left[G_f \left(\frac{\nu}{r} \right)^{I_f} \right]^{\frac{\nu}{1 - \nu}} \\
 W &= w(L) + w'(L)(L_f + \lambda L_j).
 \end{aligned} \tag{19}$$

with,

$$G_f = \exp \left(\int_0^{I_f} \log[\gamma_m(x)] dx + \int_{I_f}^1 \log[\gamma_\ell(x)] dx \right) \quad (20)$$

and the unknowns are L_f and W . Notice that both I_f and, therefore, G_f are also functions of W . We need to show that, as Common Ownership, λ , increases, employment decreases and automation increases. We will focus on proving that employment decreases and the marginal cost of labor W increases. Indeed, an increase in W is necessarily linked with an increase in automation I_f —see the FOC in 17. To proceed with the analytical proof, we need to specify the functional forms of the productivity schedules. These are,

$$\gamma_m(x) = e^{\alpha_m x} \quad (21)$$

$$\gamma_\ell(x) = e^{\alpha_\ell x} \quad (22)$$

with, crucially, $\alpha_\ell > \alpha_m$. This implies that the expression for I_f is,

$$I_f = \frac{1}{\alpha_\ell - \alpha_m} \log \left(\frac{W}{r} \right) \quad (23)$$

To characterize the solution of the system in 19, we first prove that the function represented by the first equation, $L_f = g_d(W)$ is decreasing, that is, as the marginal cost of labor goes up, the labor demand decreases. To begin, we take logs,

$$\log(L_f) = \log(1 - I_f) + \frac{I_f \nu}{1 - \nu} (\log(W) - \log(\nu) + \log\left(\frac{\nu}{r}\right)) - \frac{1}{1 - \nu} \log(W) + \frac{1}{1 - \nu} \log(\nu) + \frac{\nu}{1 - \nu} \log(G_f). \quad (24)$$

We then take the derivative with respect to W ,

$$\frac{\partial}{\partial W} \log(L_f) = \frac{\partial I_f}{\partial W} \left[\frac{\nu}{1 - \nu} \log\left(\frac{W}{r}\right) - \frac{1}{1 - I_f} \right] + \frac{I_f \nu - 1}{(1 - \nu)W} + \frac{\nu}{1 - \nu} \frac{1}{G_f} \frac{\partial G_f}{\partial W}, \quad (25)$$

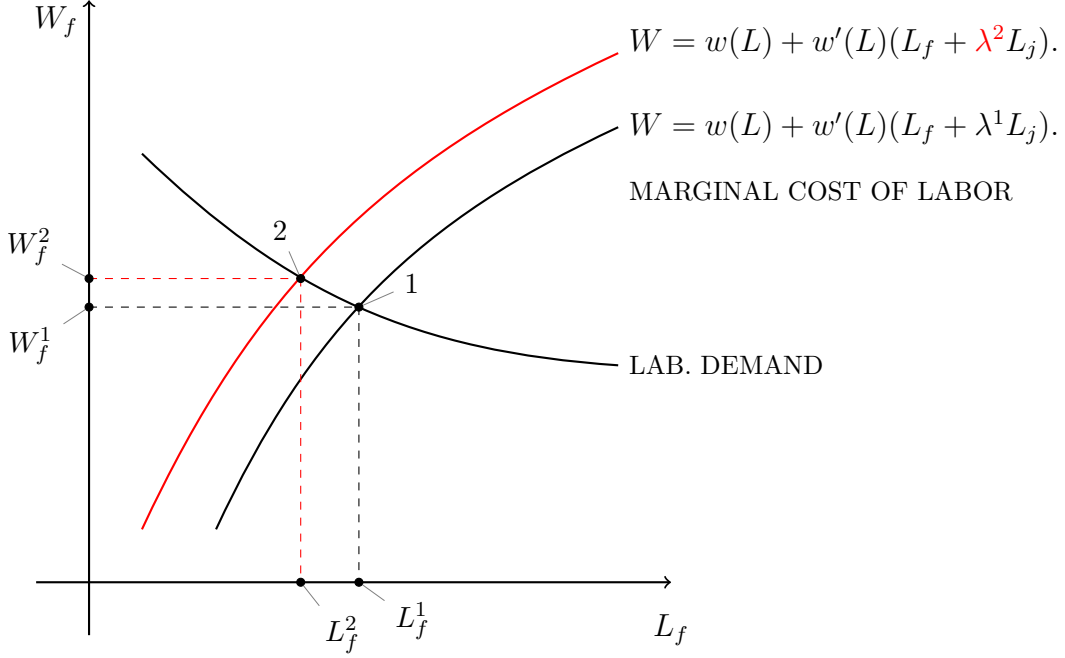
and substitute the derivative of G_f

$$\frac{\partial G_f}{\partial W} = -G_f \log\left(\frac{W}{r}\right) \frac{\partial I_f}{\partial W}. \quad (26)$$

We obtain,

$$\frac{\partial}{\partial W} \log(L_f) = \frac{\partial I_f}{\partial W} \left[\frac{\nu}{1 - \nu} \log\left(\frac{W}{r}\right) - \frac{1}{1 - I_f} \right] + \frac{I_f \nu - 1}{(1 - \nu)W} - \frac{\nu}{1 - \nu} \log\left(\frac{W}{r}\right) \frac{\partial I_f}{\partial W}. \quad (27)$$

Figure 10
LABOR DEMAND AND MARGINAL FACTOR COST CURVES



Notes: This figure plots the labor demand curve and the curve of the marginal factor cost of labor for two different values of common ownership, $\lambda_2 > \lambda_1$. It shows that as common ownership goes up employment decreases and the marginal cost of labor increases.

By rearranging, we finally derive,

$$\frac{\partial}{\partial W} \log(L_f) = -\frac{\partial I_f}{\partial W} \frac{1}{1 - I_f} + \frac{I_f \nu - 1}{(1 - \nu)W}. \quad (28)$$

Which is always negative because $0 < I < 1$ and $0 < \nu < 1$. As the function $L_f = g_d(W)$ is decreasing, the inverse $W = g_d^{-1}(L_f)$ exists and is also decreasing. As the second equation of the system 19 is increasing, we can plot the two functions and derive the properties of the solution.

In Figure 10, we plot two scenarios. One in which the level of Common Ownership is λ^1 and a second one with higher Common Ownership, $\lambda^2 > \lambda^1$. The change in CO does not affect the labor demand *curve*. As CO shifts the labor supply curve upwards, and because of the proven properties of the labor demand curve, the optimal employment of firm j decreases, and the marginal cost of labor goes up. As can be easily seen by looking at equation (23), an increase in W_f implies an increase in I_f .

It is straightforward to generalize this result to the model with a generic number of firms and local labor markets. In the general model, an increase in a pairwise degree of common

ownership λ_{fj} increases automation in every overlapping local labor market, i.e.,

$$\frac{dI_f^c}{d\lambda_{fj}} > 0,$$

and reduces employment, i.e.,

$$\frac{dL_f^c}{d\lambda_{fj}} < 0,$$

for all $c \in \mathcal{C}_f \cap \mathcal{C}_j$. Therefore, firm-level automation,

$$I_f \equiv \frac{1}{|\mathcal{C}_f|} \sum_{c \in \mathcal{C}_f} I_f^c,$$

increases. Likewise, total firm employment,

$$L_f \equiv \sum_{c \in \mathcal{C}_f} L_f^c,$$

decreases. □

B OLS Estimation

In this section of the Appendix we present OLS estimates. We test Hypothesis 1 through a set of two-way fixed effect regressions. These regressions, although probably biased and suffering from endogeneity, allow us to see if we observe a general association in our panel between common ownership within local labor markets (*CindexLM*) and the automation strategy of firms (*AutoRatio*) on the firm level. To this end, we estimate the model in equation (29).

$$AutoRatio_{j(t+\tau)} = \beta_0 + \beta_1 CindexLM_{jt} + \gamma X_{jt} + \alpha_j + \delta_{st} + \epsilon_{jt} \quad (29)$$

$AutoRatio_{j(t+\tau)}$ is the τ th lead of our measure of the automation content of innovation as defined in Section 3.2.2. Although common owners holding shares in firms within the same local labor market may affect the investment strategy of firms contemporaneously, we expect these changes to translate into different innovation outcomes in the future, because of time lags between starting research projects and the resulting patent application in the case of success. Therefore, we consider $\tau = 1, 2, 3, \dots, 6$ in the OLS panel regression. $CindexLM_{jt}$ is the common ownership measure at the firm-year level defined in section 3.2.1. Furthermore, we include X , the control variables discussed previously, and a set of firm (j), industry (s), and year (t) fixed effects to control for common shocks, e.g., industry spillovers from automation-relevant technologies or industry-specific trends in the technological feasibility frontier. The results are shown in Table 6. As the results indicate, on average, firms' future automation-related innovation output is positively correlated with their current common ownership with labor market rivals and is significantly higher three to five years ahead. The results suggest a humped-shape relationship between *CindexLM* and the future automation content of a firm's innovation output. Also, the signs of the coefficients of the control variables are sensible. Larger firms are more likely to invest in automation, probably due to economies of scale; while older firms produce relatively less automation innovation. However, as mentioned before, these results could be biased or driven by unobservable heterogeneity.

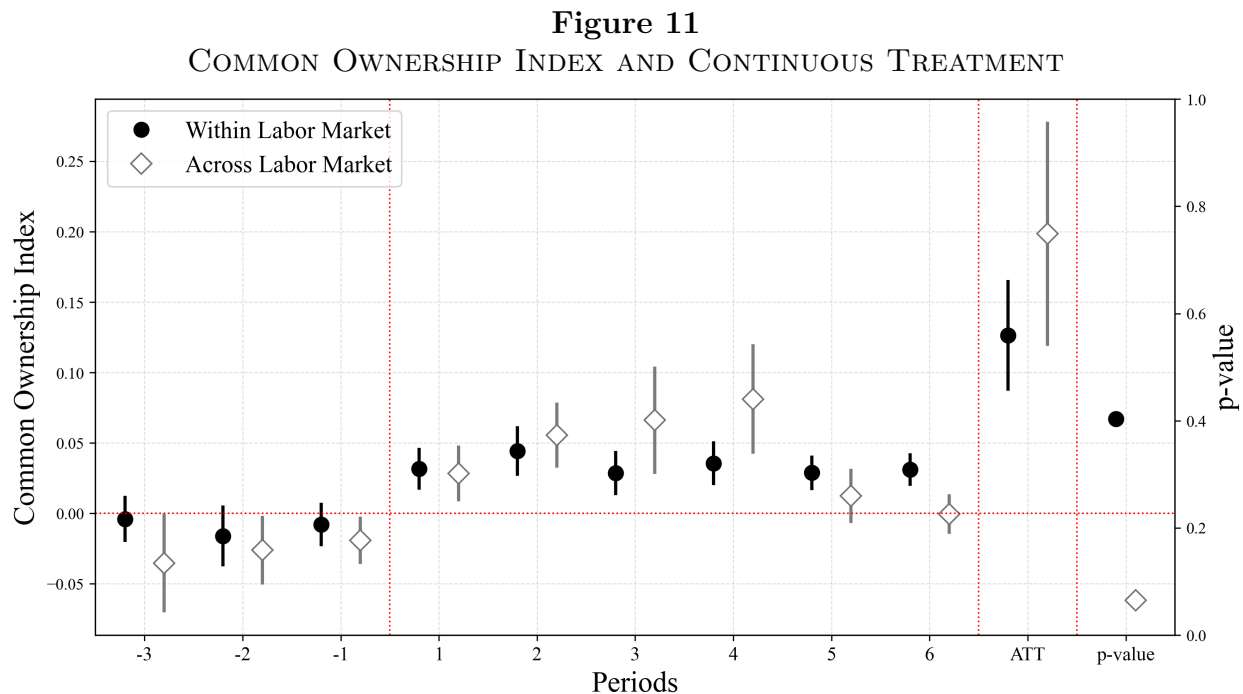
Table 6
OLS REGRESSION RESULTS

	Yt+1	Yt+2	Yt+3	Yt+4	Yt+5	Yt+6
<i>CindexLM</i>	6.059 (6.455)	10.240 (7.100)	17.496** (7.793)	19.821** (8.639)	18.753** (9.447)	13.155 (10.607)
<i>InstOwn</i>	0.062 (0.074)	-0.004 (0.075)	-0.026 (0.077)	0.043 (0.078)	0.027 (0.082)	-0.081 (0.088)
<i>R&D</i>	0.115** (0.045)	0.064 (0.046)	0.014 (0.043)	-0.017 (0.055)	-0.038 (0.060)	0.046 (0.055)
<i>FirmSize</i>	0.054** (0.022)	0.040* (0.021)	0.024 (0.021)	0.005 (0.021)	-0.004 (0.022)	0.009 (0.023)
<i>FirmAge</i>	-0.093** (0.044)	-0.080* (0.045)	-0.092* (0.047)	-0.079 (0.049)	-0.121** (0.051)	-0.160*** (0.051)
<i>PPEAssets</i>	-0.023 (0.120)	-0.039 (0.129)	-0.114 (0.135)	-0.122 (0.138)	-0.162 (0.140)	-0.210 (0.141)
<i>LogSales</i>	0.016 (0.030)	0.025 (0.033)	0.022 (0.034)	0.029 (0.034)	0.003 (0.035)	0.015 (0.034)
<i>TobinsQ</i>	0.003 (0.002)	0.006*** (0.002)	0.007*** (0.002)	0.004* (0.002)	0.001 (0.002)	0.002 (0.002)
<i>MarketCap</i>	0.000* (0.000)	0.000** (0.000)	0.000* (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
<i>CAPEXAssets</i>	-0.326* (0.191)	-0.393** (0.186)	0.184 (0.196)	0.275 (0.188)	0.320 (0.199)	0.365* (0.200)
<i>CapitalIntensity</i>	0.000 (0.001)	0.001*** (0.000)	0.006** (0.003)	0.002 (0.002)	0.001 (0.002)	0.000 (0.003)
<i>LeverageValue</i>	0.017 (0.020)	0.045 (0.037)	0.005 (0.031)	0.009 (0.046)	0.013 (0.073)	-0.002 (0.072)
<i>Cash</i>	0.029 (0.059)	-0.071 (0.062)	-0.120* (0.064)	-0.029 (0.062)	-0.052 (0.067)	-0.072 (0.070)
<i>Profitability</i>	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
<i>Constant</i>	0.004 (0.244)	0.140 (0.251)	0.249 (0.262)	0.305 (0.267)	0.372 (0.274)	0.528** (0.265)
Observations	18042	16613	15137	13700	12304	10992
<i>R</i> ² Adjusted	0.734	0.742	0.753	0.764	0.771	0.782

Notes: This table presents OLS estimates of firms' automation strategy on common ownership with local labor rivals. Standard errors in parentheses are clustered at the firm level. Significance levels are indicated as follows: * p<0.1, ** p<0.05, *** p<0.01.

C Additional Figures

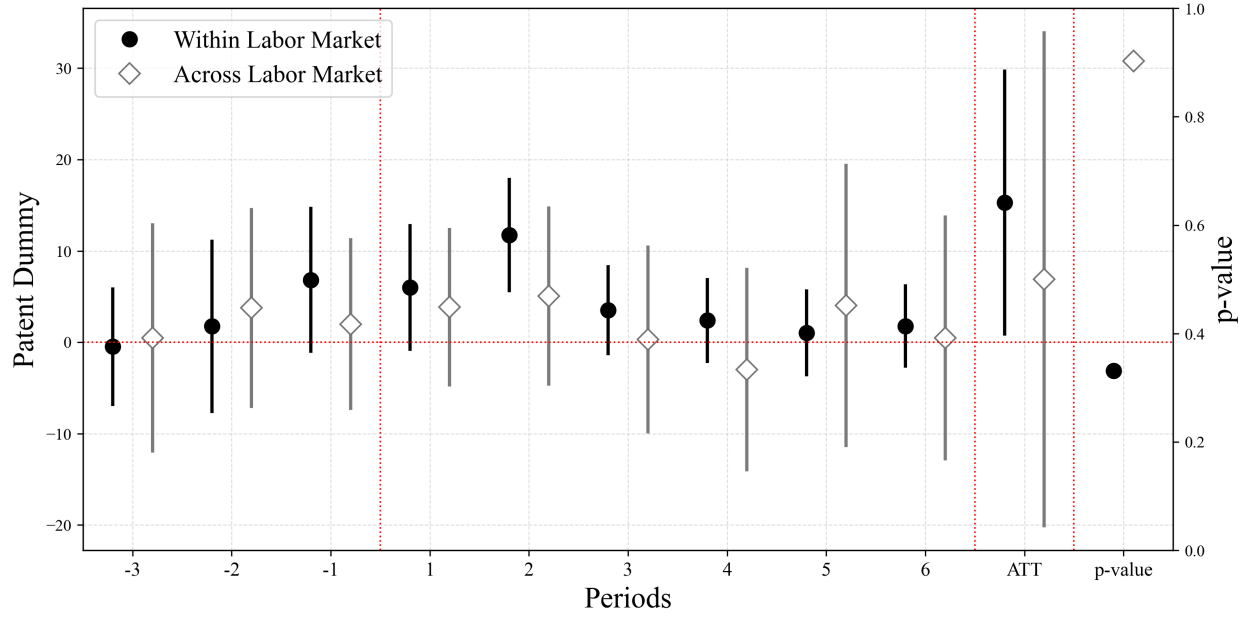
First-stage regression



Notes: This figure reports the dynamic and average total treatment (ATT) effects of being treated by an institutional merger that likely increases common ownership within (*ContTreatLM*) and across (*ContTreatNotLM*) labor markets on the raw firm-level common ownership regarding LM rivals (*CindexLM*, within) and on common ownership across labor markets (*CindexNotLM*), respectively. The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

Patent Outcome Measure

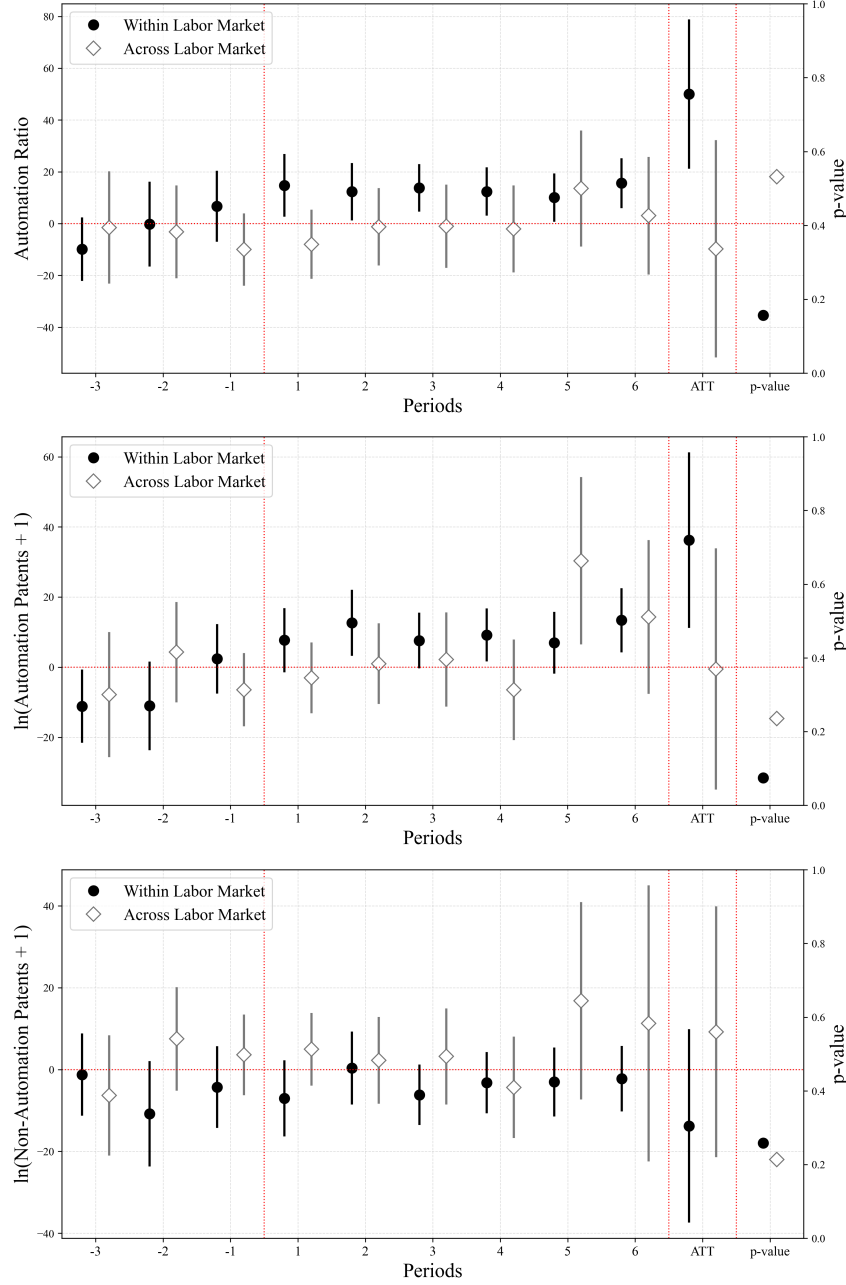
Figure 12
PATENT RESULTS: BINARY MODEL



Notes: This Figure shows the dynamic effects of the within and across local labor market treatment models on the propensity of firms to patent. The outcome measure used is a binary indicator for whether firm j applied for a patent (that was subsequently granted) in year t . The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

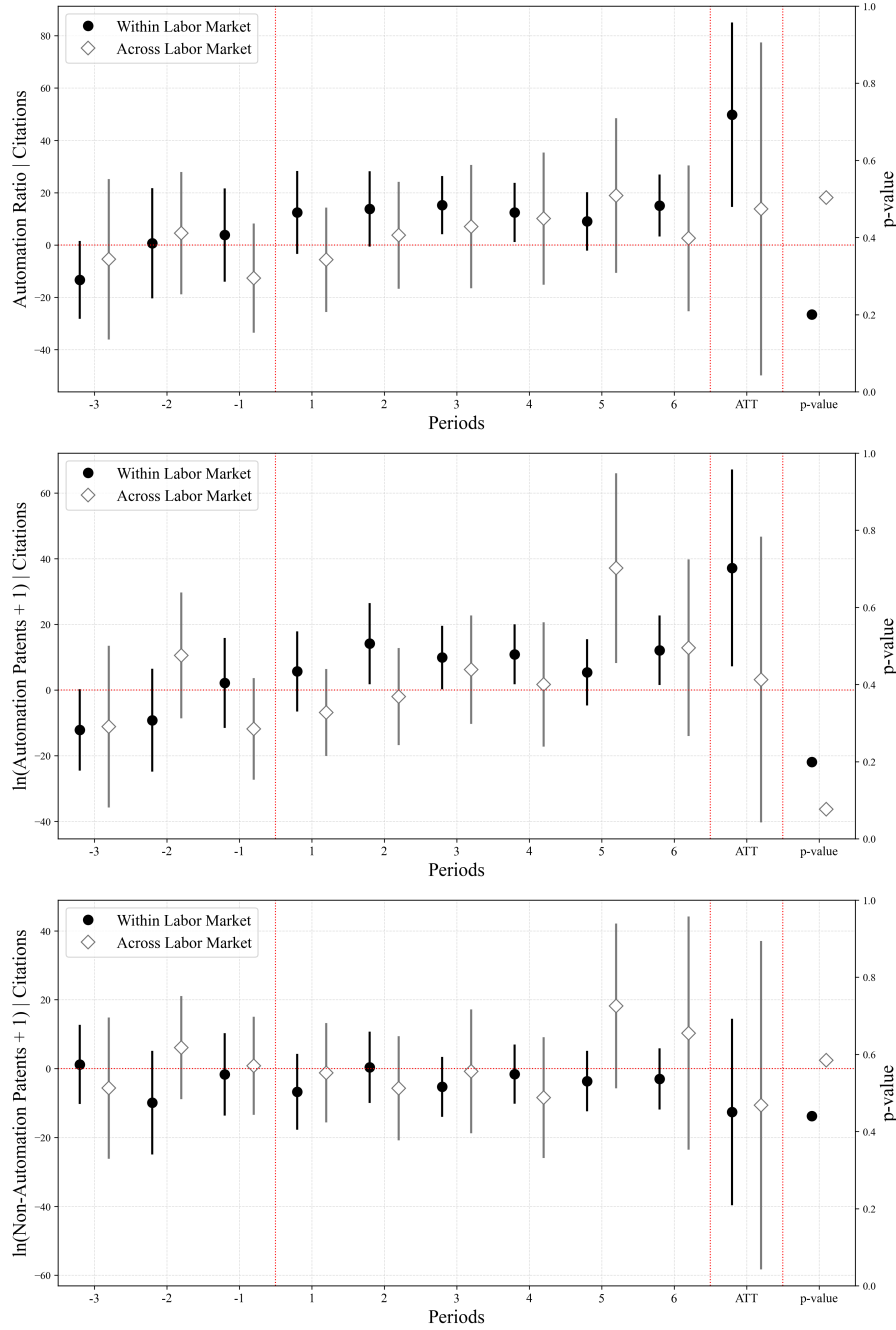
Dynamic Results

Figure 13
DYNAMIC RESULTS FOR CONTINUOUS MODEL



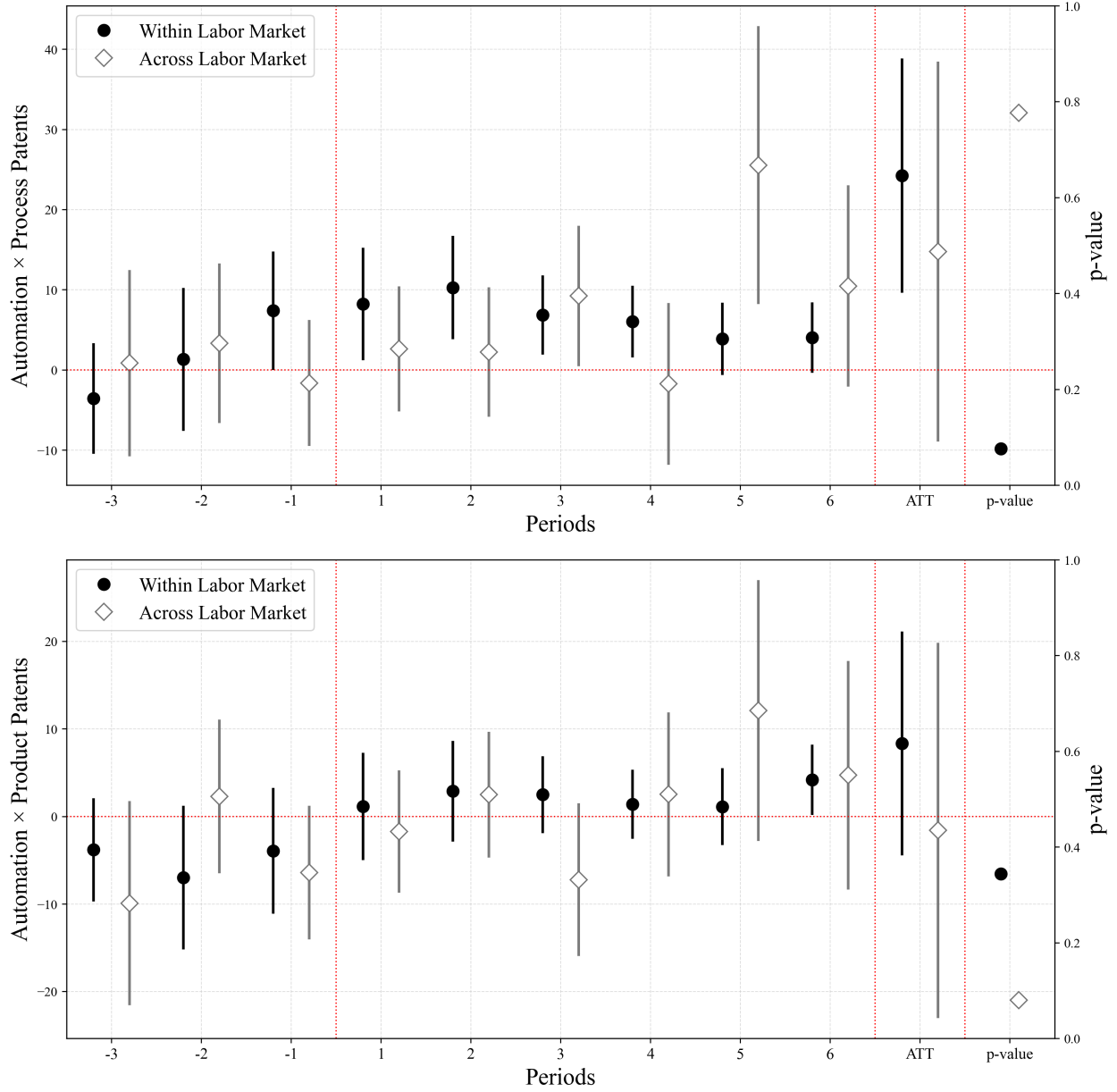
Notes: This Figure shows the dynamic effects for the treatment effects under the continuous treatment model. Panel A) plots the effect on the log ratio of (automation patents + 1) to (non-automation patents + 1). Panel B) and C) then present the separate results for the log of (automation patents + 1) and (non-automation patents + 1) respectively. The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

Figure 14
DYNAMIC RESULTS FOR CONTINUOUS MODEL: CITATION WEIGHTED



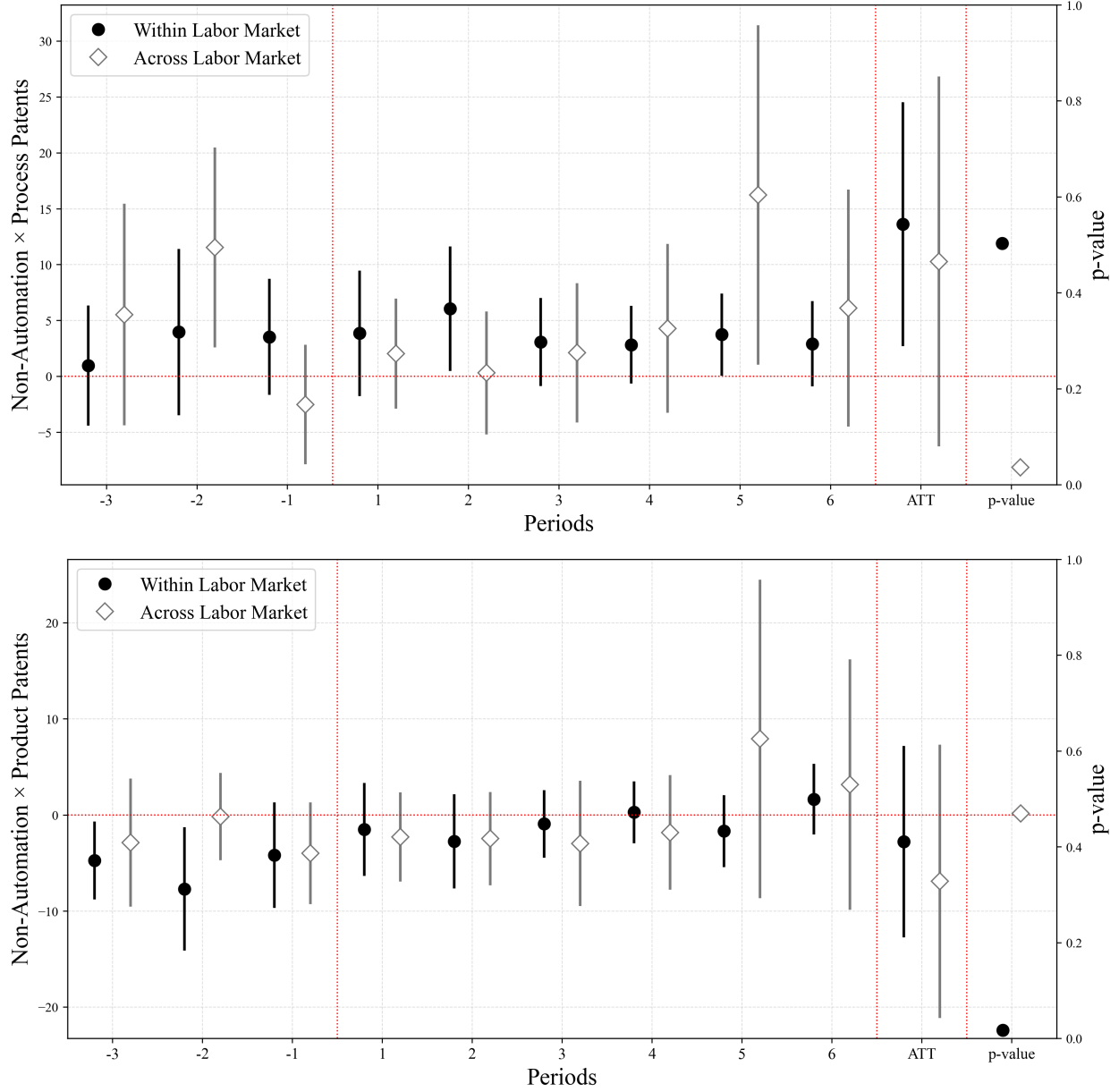
Notes: This Figure shows the dynamic effects for the treatment effects under the continuous treatment model. Panel A) plots the effect on the log ratio of (automation patents + 1) to (non-automation patents + 1), weighted by citation counts. Panel B) and C) then present the separate results for the log of (automation patents + 1) and (non-automation patents + 1) weighted by citation counts, respectively. The estimation model is outlined in [De Chaisemartin and d'Haultfoeulle \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

Figure 15
DYNAMIC RESULTS FOR AUTOMATION $\times$ PROCESS PATENTS



Notes: This Figure shows the dynamic effects for the treatment effects under the continuous treatment model for automation patents, split by product and process. The outcome measure for panel A) is a binary indicator for whether firm j applied for an automation process patent (that was subsequently granted) in year t . The outcome measure for panel A) is a binary indicator for whether firm j applied for an automation product patent (that was subsequently granted) in year t . The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

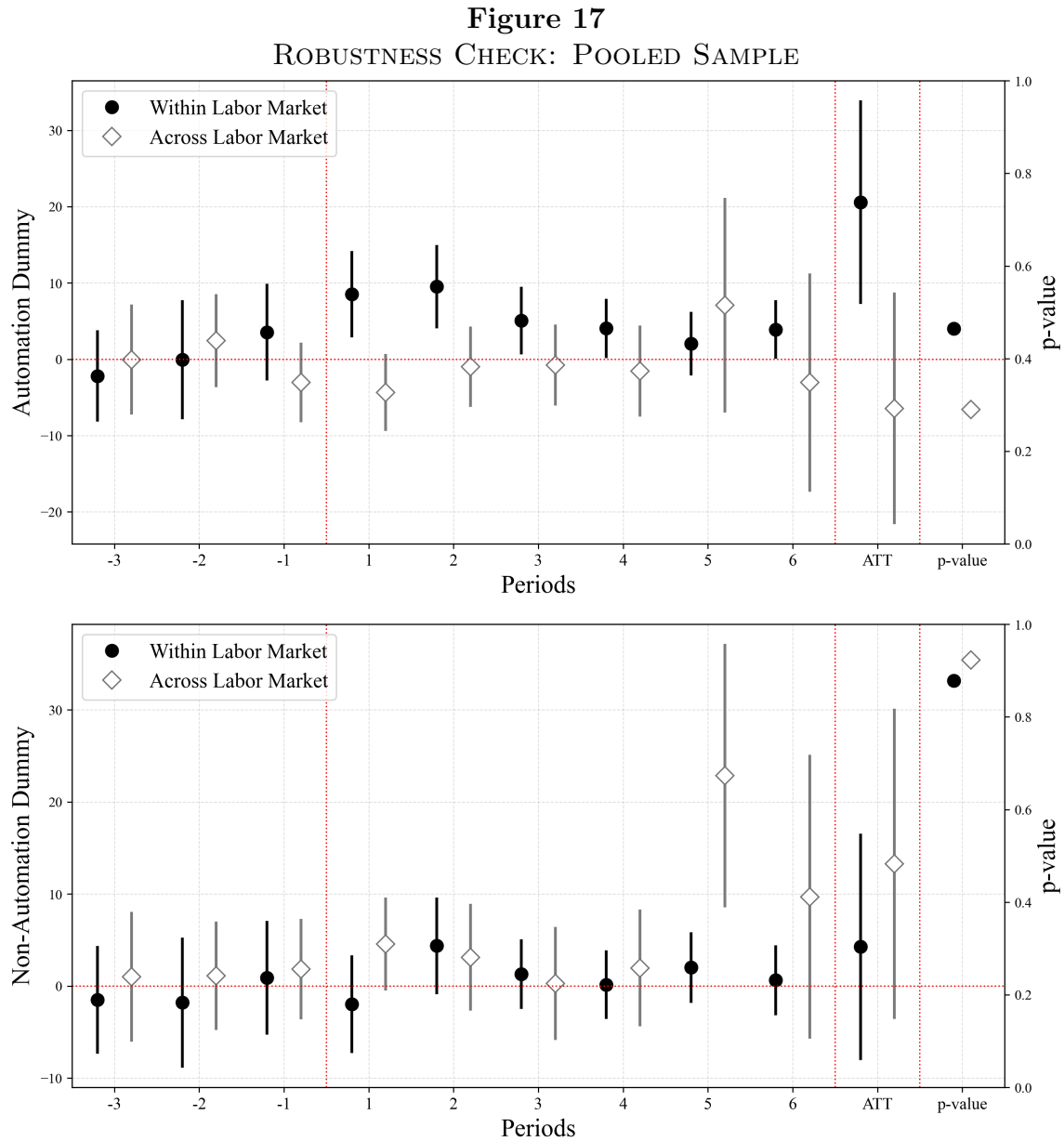
Figure 16
DYNAMIC RESULTS FOR NON-AUTOMATION $\times$ PROCESS PATENTS



Notes: This Figure shows the dynamic effects for the treatment effects under the continuous treatment model for non-automation patents, split by product and process. The outcome measure for panel A is a binary indicator for whether firm j applied for an non-automation process patent (that was subsequently granted) in year t . The outcome measure for panel A is a binary indicator for whether firm j applied for an non-automation product patent (that was subsequently granted) in year t . The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

D Robustness

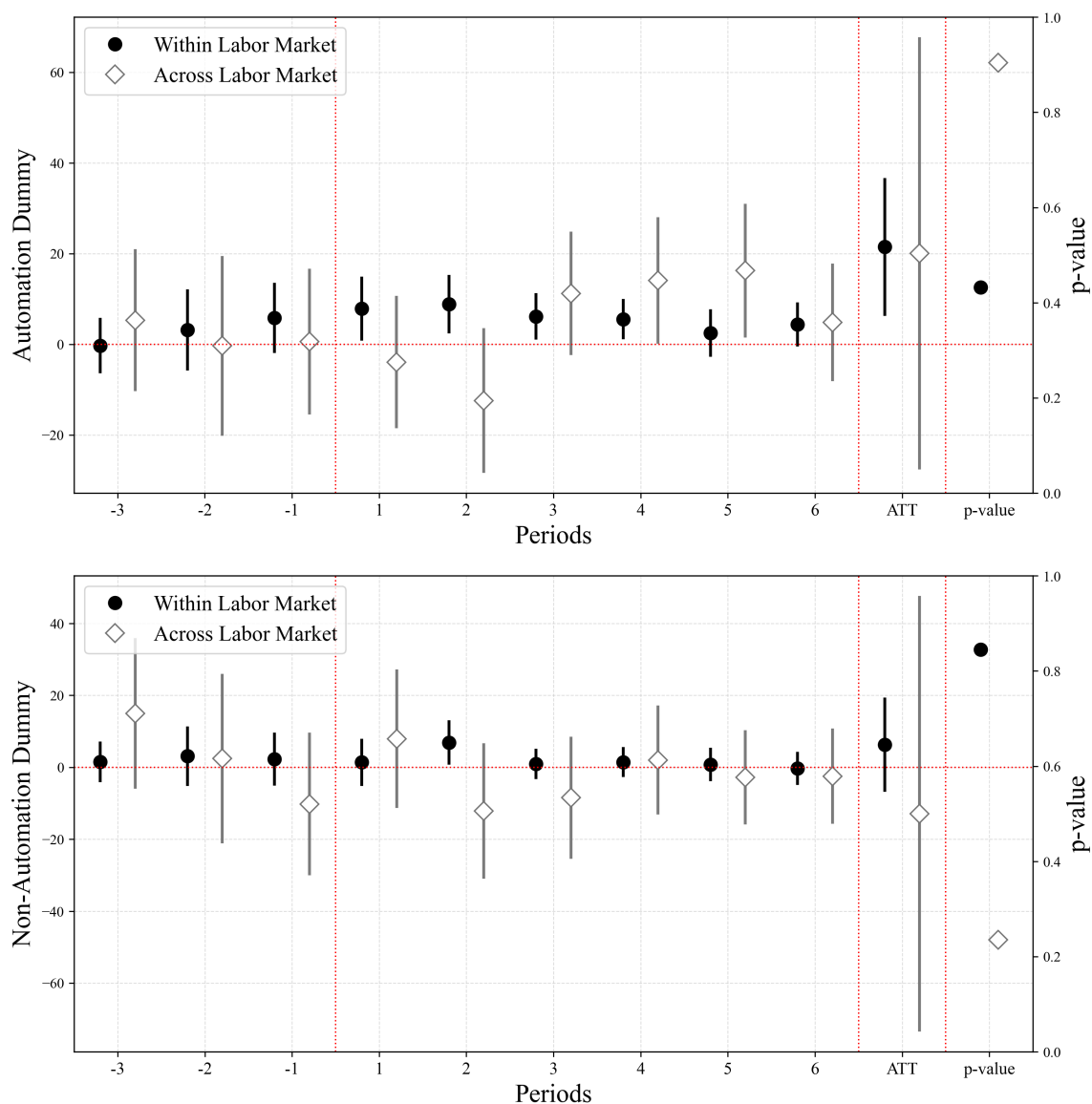
Pooled Sample



Notes: A figure plotting the dynamic effects and average total treatment (ATT) effects for the treatment model with two binary outcomes in the pooled sample. Panel A) reports the results for automation patents and panel B) for non-automation patents. This sample contains observations of those firms treated by *ContTreatnotLM* in some years. The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

Using data before the onset of the financial crisis

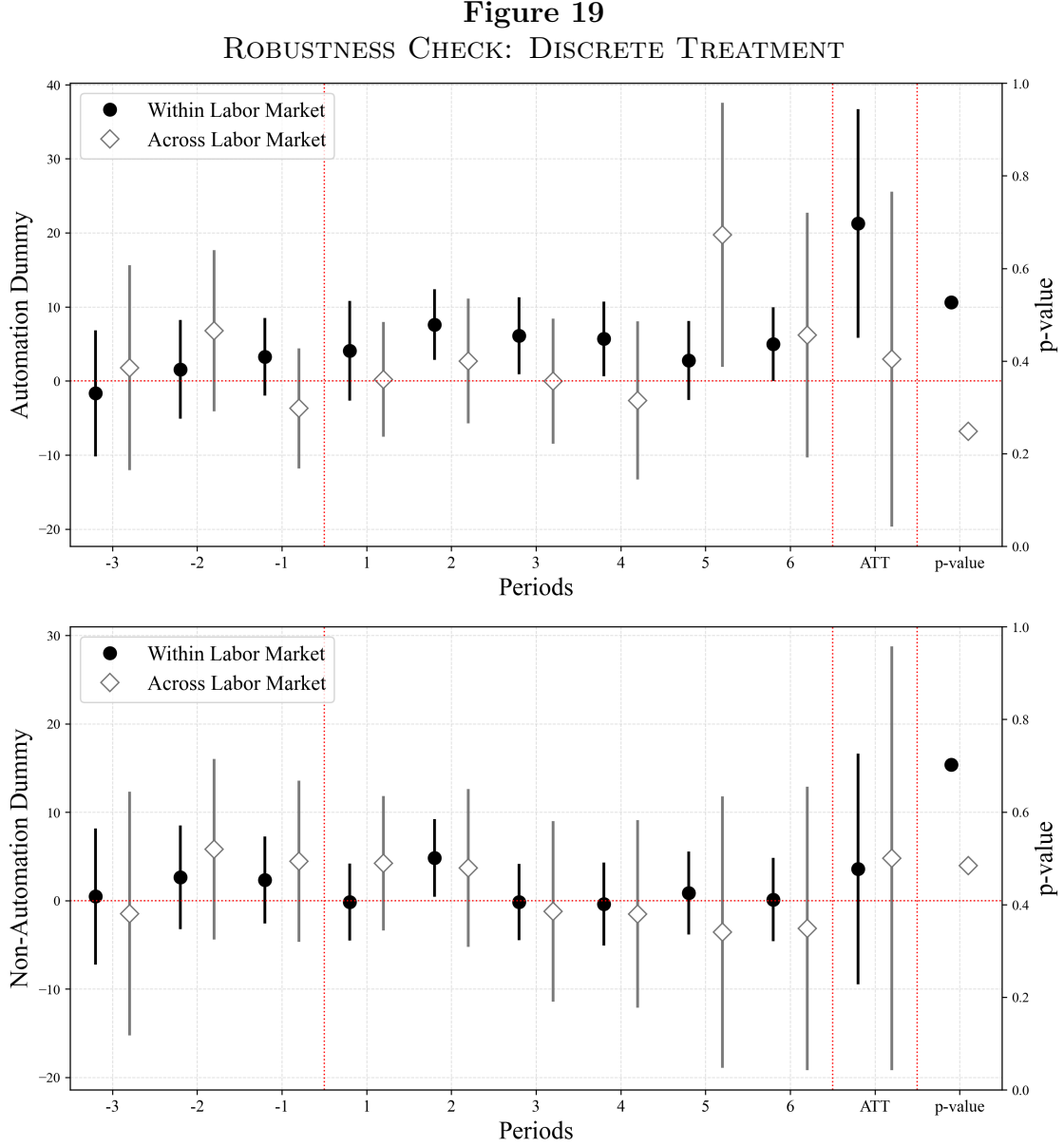
Figure 18
ROBUSTNESS CHECK: PRE-2007 SAMPLE



Notes: A figure plotting the dynamic effects and average total treatment (ATT) effects for the treatment model with two binary outcomes using data up to 2006, i.e., before the onset of the financial crisis. Panel A) reports the results for automation patents and panel B) for non-automation patents. The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

Using the binary treatment setup

In this Section, we present the results of the DID analysis employing the binary treatment variable $TreatLM$ as defined in Section 3.2.5. The results are shown in Figure 19.



Notes: A figure plotting the dynamic effects and average total treatment (ATT) effects with two binary outcomes using the binary treatment indicator model. Panel A) reports the results for automation patents and panel B) for non-automation patents. The estimation model is outlined in [De Chaisemartin and d'Haultfoeuille \(2024\)](#), the model controls for the full set of control variables listed in section 3.2.6.

E Database Construction

Matching establishment level information with Compustat. The 2020 version of the National Establishments Time Series (NETS) provides the legal business names of establishments. We employ the legal business names of these establishments for cross-referencing with the Compustat database in our empirical analysis.

We utilize fuzzy matching, employing a similarity threshold of 90%, to align company names between the two databases. Subsequently, we conduct manual verification to ensure the precision of these matches. With this methodology, we successfully merge 353,818 establishments. It results in a dataset of 4,231,721 establishment-year observations for the spanning period 1990-2020, each containing no missing information on employee count and geographical location.

F Full Regression Result Tables

Table 7: First-Stage Results: Effect of Institutional Investor Mergers on Common Ownership Within Labor Markets

	CindexLM
Placebo $t - 3$	-0.004 (0.008)
Placebo $t - 2$	-0.016 (0.010)
Placebo $t - 1$	-0.008 (0.007)
Effect $t + 1$	0.032*** (0.007)
Effect $t + 2$	0.044*** (0.008)
Effect $t + 3$	0.029*** (0.007)
Effect $t + 4$	0.036*** (0.007)
Effect $t + 5$	0.029*** (0.006)
Effect $t + 6$	0.031*** (0.005)
Average Total Effect	0.126*** (0.019)
Joint Placebo Test	$p = 0.403$
Observations	9,431

Notes: This table reports the first-stage effects of institutional investor mergers on firm-level common ownership within labour markets. The dependent variable is *CindexLM* and the treatment is *Cont-TreatLM*. Coefficients are scaled by treatment intensity (0.022×100) and expressed in percentage points. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: First-Stage Results: Effect of Institutional Investor Mergers on Common Ownership Across Labor Markets

	CindexNotLM
Placebo $t - 3$	-0.035^{**} (0.017)
Placebo $t - 2$	-0.026^{**} (0.012)
Placebo $t - 1$	-0.019^{**} (0.008)
Effect $t + 1$	0.028^{***} (0.010)
Effect $t + 2$	0.056^{***} (0.011)
Effect $t + 3$	0.066^{***} (0.019)
Effect $t + 4$	0.081^{***} (0.019)
Effect $t + 5$	0.012 (0.009)
Effect $t + 6$	-0.000 (0.007)
Average Total Effect	0.199^{***} (0.040)
Joint Placebo Test	$p = 0.065$
Observations	6,016

Notes: This table reports the first-stage effects of institutional investor mergers on firm-level common ownership across labour markets. The dependent variable is *CindexNotLM* and the treatment is *Con-tTreatNotLM*. Coefficients are scaled by treatment intensity (0.025×100) and expressed in percentage points. Standard errors clustered at firm level in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 9: Main Automation Outcomes: Within vs. Across Labor Market Effects

	(1) AutoRatio	(2) Auto Binary	(3) NonAuto Binary
Panel A: Within Labor Market (Same CZ)			
Placebo $t - 3$	-9.90 (6.06)	-1.31 (3.37)	0.38 (3.05)
Placebo $t - 2$	-0.23 (8.14)	2.19 (4.60)	3.66 (4.05)
Placebo $t - 1$	6.69 (6.78)	4.76 (3.78)	3.41 (3.55)
Effect $t + 1$	14.76** (5.95)	8.17** (3.32)	0.11 (3.09)
Effect $t + 2$	12.31** (5.42)	11.02*** (3.15)	6.41** (2.95)
Effect $t + 3$	13.78*** (4.47)	5.98** (2.49)	-0.15 (2.07)
Effect $t + 4$	12.38*** (4.55)	5.19** (2.26)	-0.36 (2.11)
Effect $t + 5$	10.03** (4.54)	2.57 (2.43)	0.80 (2.14)
Effect $t + 6$	15.61*** (4.70)	4.45** (2.19)	0.11 (2.07)
Average Total Effect	50.01*** (14.49)	22.71*** (7.60)	3.60 (6.60)
Joint Placebo Test	$p = 0.156$	$p = 0.527$	$p = 0.702$
Observations	9,431	9,431	9,431
Panel B: Across Labor Markets (Different CZ)			
Placebo $t - 3$	-1.50 (10.86)	1.51 (5.81)	-1.23 (5.80)
Placebo $t - 2$	-3.21 (8.91)	5.93 (4.77)	5.10 (4.49)
Placebo $t - 1$	-10.03 (6.89)	-3.53 (3.86)	4.27 (4.37)
Effect $t + 1$	-7.98 (6.61)	0.22 (3.76)	4.14 (3.72)
Effect $t + 2$	-1.24 (7.38)	2.56 (3.98)	3.50 (4.25)
Effect $t + 3$	-1.01 (7.97)	-0.03 (3.95)	-1.13 (4.81)
Effect $t + 4$	-2.10 (8.35)	-2.45 (5.00)	-1.41 (4.98)
Effect $t + 5$	13.55 (11.22)	16.18** (7.37)	-2.91 (6.35)
Effect $t + 6$	3.05 (11.37)	4.92 (6.62)	-2.50 (6.43)
Average Total Effect	-9.75 (21.19)	2.92 (11.31)	4.74 (12.01)
Joint Placebo Test	$p = 0.532$	$p = 0.248$	$p = 0.484$
Observations	6,016	6,016	6,016

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Panel A shows effects of within-labor-market common ownership (same commuting zone). Panel B shows effects of across-labor-market common ownership (different commuting zones). Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Process vs. Product Innovation: Within vs. Across Labor Market Effects

	(1) Auto×Process	(2) Auto×Product	(3) NonAuto×Process	(4) NonAuto×Product
Panel A: Within Labor Market (Same CZ)				
Placebo $t - 3$	−3.58 (3.44)	−3.82 (2.93)	0.95 (2.68)	−4.74** (2.00)
Placebo $t - 2$	1.31 (4.46)	−6.99* (4.11)	3.95 (3.73)	−7.72** (3.21)
Placebo $t - 1$	7.38** (3.68)	−3.94 (3.58)	3.52 (2.59)	−4.21 (2.74)
Effect $t + 1$	8.22** (3.50)	1.12 (3.05)	3.84 (2.81)	−1.52 (2.40)
Effect $t + 2$	10.27*** (3.21)	2.87 (2.86)	6.04** (2.79)	−2.76 (2.44)
Effect $t + 3$	6.84*** (2.44)	2.48 (2.17)	3.06 (1.95)	−0.93 (1.73)
Effect $t + 4$	6.01*** (2.20)	1.38 (1.94)	2.82* (1.71)	0.26 (1.57)
Effect $t + 5$	3.87* (2.22)	1.11 (2.17)	3.73** (1.82)	−1.70 (1.85)
Effect $t + 6$	4.02* (2.15)	4.18** (1.97)	2.90 (1.89)	1.63 (1.81)
Average Total Effect	24.23*** (7.38)	8.32 (6.45)	13.61** (5.51)	−2.78 (5.02)
Joint Placebo Test	$p = 0.076$	$p = 0.344$	$p = 0.503$	$p = 0.017$
Observations	9,431	9,431	7,142	8,154
Panel B: Across Labor Markets (Different CZ)				
Placebo $t - 3$	0.83 (5.84)	−9.91* (5.87)	5.52 (5.00)	−2.89 (3.34)
Placebo $t - 2$	3.32 (5.00)	2.28 (4.41)	11.53** (4.50)	−0.18 (2.25)
Placebo $t - 1$	−1.64 (3.93)	−6.42* (3.81)	−2.54 (2.67)	−4.00 (2.63)
Effect $t + 1$	2.61 (3.89)	−1.73 (3.48)	2.03 (2.45)	−2.31 (2.30)
Effect $t + 2$	2.23 (4.03)	2.48 (3.59)	0.30 (2.75)	−2.48 (2.41)
Effect $t + 3$	9.22** (4.38)	−7.23* (4.38)	2.10 (3.13)	−2.97 (3.26)
Effect $t + 4$	−1.75 (5.06)	2.52 (4.70)	4.28 (3.80)	−1.83 (2.97)
Effect $t + 5$	25.54*** (8.76)	12.08 (7.52)	16.23** (7.69)	7.91 (8.39)
Effect $t + 6$	10.46* (6.32)	4.70 (6.59)	6.10 (5.36)	3.15 (6.59)
Average Total Effect	14.75 (12.01)	−1.59 (10.86)	10.27 (8.39)	−6.91 (7.19)
Joint Placebo Test	$p = 0.776$	$p = 0.080$	$p = 0.036$	$p = 0.469$
Observations	6,016	6,016	4,601	5,074

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. Process innovations automate production steps; product innovations create new automated products. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Employment and Patenting: Within vs. Across Labor Market Effects

	(1) Employment	(2) Patent
Panel A: Within Labor Market (Same CZ)		
Placebo $t - 3$	2.63 (2.80)	-0.48 (3.23)
Placebo $t - 2$	-0.09 (3.68)	1.74 (4.75)
Placebo $t - 1$	1.69 (2.66)	6.83* (3.98)
Effect $t + 1$	-2.58 (2.49)	5.99* (3.45)
Effect $t + 2$	-9.14*** (2.35)	11.74*** (3.09)
Effect $t + 3$	-4.93*** (1.73)	3.51 (2.42)
Effect $t + 4$	-5.50*** (1.87)	2.38 (2.29)
Effect $t + 5$	-5.16** (2.18)	1.03 (2.34)
Effect $t + 6$	-9.12*** (2.33)	1.78 (2.23)
Average Total Effect	-22.82*** (5.91)	15.30** (7.34)
Joint Placebo Test	$p = 0.654$	$p = 0.331$
Observations	8,454	9,431
Panel B: Across Labor Markets (Different CZ)		
Placebo $t - 3$	-5.93 (5.48)	0.48 (6.32)
Placebo $t - 2$	-11.69** (5.93)	3.75 (5.49)
Placebo $t - 1$	-7.33* (4.27)	1.99 (4.70)
Effect $t + 1$	-3.67 (4.79)	3.84 (4.34)
Effect $t + 2$	-3.29 (3.63)	5.06 (4.92)
Effect $t + 3$	-10.05** (4.77)	0.31 (5.15)
Effect $t + 4$	-4.70 (4.75)	-2.99 (5.59)
Effect $t + 5$	-0.75 (4.79)	4.02 (7.81)
Effect $t + 6$	-5.01 (5.05)	0.46 (6.75)
Average Total Effect	-19.25 (11.83)	6.89 (13.76)
Joint Placebo Test	$p = 0.150$	$p = 0.903$
Observations	5,694	6,016

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. Employment growth is log change in employment. Patent binary indicates whether firm patents in that year. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Continuous Measures (Logs): Within vs. Across Labor Market Effects

	(1) AutoRatio	(2) ln(Auto)	(3) ln(NonAuto)
Panel A: Within Labor Market (Same CZ)			
Placebo $t - 3$	-9.90 (6.06)	-11.14** (5.17)	-1.24 (4.99)
Placebo $t - 2$	-0.23 (8.14)	-11.03* (6.29)	-10.80* (6.42)
Placebo $t - 1$	6.69 (6.78)	2.40 (4.89)	-4.29 (4.96)
Effect $t + 1$	14.76** (5.95)	7.71* (4.50)	-7.05 (4.61)
Effect $t + 2$	12.31** (5.42)	12.65*** (4.65)	0.35 (4.40)
Effect $t + 3$	13.78*** (4.47)	7.60* (3.90)	-6.19* (3.63)
Effect $t + 4$	12.38*** (4.55)	9.18** (3.70)	-3.20 (3.67)
Effect $t + 5$	10.03** (4.54)	6.98 (4.33)	-3.05 (4.15)
Effect $t + 6$	15.61*** (4.70)	13.39*** (4.50)	-2.22 (3.95)
Average Total Effect	50.01*** (14.49)	36.23*** (12.61)	-13.79 (11.91)
Joint Placebo Test	$p = 0.156$	$p = 0.075$	$p = 0.258$
Observations	9,431	9,431	9,431
Panel B: Across Labor Markets (Different CZ)			
Placebo $t - 3$	-1.50 (10.86)	-7.84 (8.94)	-6.34 (7.35)
Placebo $t - 2$	-3.21 (8.91)	4.27 (7.15)	7.48 (6.31)
Placebo $t - 1$	-10.03 (6.89)	-6.43 (5.16)	3.60 (4.89)
Effect $t + 1$	-7.98 (6.61)	-3.05 (4.99)	4.94 (4.38)
Effect $t + 2$	-1.24 (7.38)	1.00 (5.72)	2.24 (5.28)
Effect $t + 3$	-1.01 (7.97)	2.20 (6.70)	3.20 (5.85)
Effect $t + 4$	-2.10 (8.35)	-6.48 (7.15)	-4.38 (6.18)
Effect $t + 5$	13.55 (11.22)	30.35** (12.01)	16.81 (12.17)
Effect $t + 6$	3.05 (11.37)	14.32 (11.04)	11.27 (17.07)
Average Total Effect	-9.75 (21.19)	-0.53 (17.39)	9.22 (15.49)
Joint Placebo Test	$p = 0.532$	$p = 0.235$	$p = 0.214$
Observations	6,016	6,016	6,016

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. ln(Auto) and ln(NonAuto) are log counts of automation and non-automation patents. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Citation-Weighted Measures: Within vs. Across Labor Market Effects

	(1) AutoRatio-Cites	(2) ln(Auto-Cites)	(3) ln(NonAuto-Cites)
Panel A: Within Labor Market (Same CZ)			
Placebo $t - 3$	-13.32* (7.37)	-12.11** (6.16)	1.21 (5.70)
Placebo $t - 2$	0.70 (10.53)	-9.19 (7.84)	-9.89 (7.51)
Placebo $t - 1$	3.84 (8.88)	2.17 (6.83)	-1.67 (5.94)
Effect $t + 1$	12.44 (7.90)	5.69 (6.07)	-6.75 (5.47)
Effect $t + 2$	13.79* (7.14)	14.16** (6.14)	0.37 (5.13)
Effect $t + 3$	15.23*** (5.47)	9.94** (4.77)	-5.29 (4.28)
Effect $t + 4$	12.48** (5.57)	10.88** (4.49)	-1.61 (4.24)
Effect $t + 5$	9.04* (5.47)	5.40 (4.97)	-3.64 (4.32)
Effect $t + 6$	15.10*** (5.83)	12.12** (5.25)	-2.99 (4.39)
Average Total Effect	49.80*** (17.79)	37.20** (15.13)	-12.61 (13.67)
Joint Placebo Test	$p = 0.200$	$p = 0.199$	$p = 0.440$
Observations	9,431	9,431	9,431
Panel B: Across Labor Markets (Different CZ)			
Placebo $t - 3$	-5.45 (15.42)	-11.11 (12.40)	-5.66 (10.30)
Placebo $t - 2$	4.50 (11.72)	10.58 (9.62)	6.07 (7.49)
Placebo $t - 1$	-12.62 (10.44)	-11.81 (7.73)	0.81 (7.12)
Effect $t + 1$	-5.63 (9.97)	-6.84 (6.61)	-1.20 (7.20)
Effect $t + 2$	3.73 (10.22)	-2.00 (7.38)	-5.73 (7.56)
Effect $t + 3$	7.02 (11.83)	6.22 (8.25)	-0.80 (9.01)
Effect $t + 4$	10.10 (12.68)	1.70 (9.50)	-8.41 (8.80)
Effect $t + 5$	18.95 (14.88)	37.14** (14.58)	18.19 (12.06)
Effect $t + 6$	2.58 (14.00)	12.89 (13.54)	10.31 (17.12)
Average Total Effect	13.82 (32.25)	3.21 (22.02)	-10.62 (24.17)
Joint Placebo Test	$p = 0.503$	$p = 0.077$	$p = 0.585$
Observations	6,016	6,016	6,016

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. Citations weight patents by future citations received. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Pre-2007 Robustness: Within vs. Across Labor Market Effects

	(1)	(2)
	Auto Binary	NonAuto Binary
Panel A: Within Labor Market (Same CZ)		
Placebo $t - 3$	-0.27 (2.97)	1.56 (2.68)
Placebo $t - 2$	3.18 (4.42)	3.09 (4.04)
Placebo $t - 1$	5.87 (3.79)	2.31 (3.56)
Effect $t + 1$	7.90** (3.43)	1.38 (3.15)
Effect $t + 2$	8.87*** (3.12)	6.90** (2.94)
Effect $t + 3$	6.17** (2.45)	0.95 (1.97)
Effect $t + 4$	5.56*** (2.11)	1.46 (1.93)
Effect $t + 5$	2.50 (2.51)	0.79 (2.19)
Effect $t + 6$	4.39* (2.31)	-0.27 (2.14)
Average Total Effect	21.49*** (7.60)	6.32 (6.48)
Joint Placebo Test	$p = 0.432$	$p = 0.845$
Observations	8,103	8,103
Panel B: Across Labor Markets (Different CZ)		
Placebo $t - 3$	5.33 (7.84)	15.02 (10.48)
Placebo $t - 2$	-0.33 (9.94)	2.43 (11.82)
Placebo $t - 1$	0.62 (8.03)	-10.20 (9.94)
Effect $t + 1$	-3.92 (7.29)	7.94 (9.63)
Effect $t + 2$	-12.39 (7.99)	-12.14 (9.40)
Effect $t + 3$	11.25* (6.78)	-8.46 (8.47)
Effect $t + 4$	14.10** (6.94)	2.03 (7.54)
Effect $t + 5$	16.26** (7.36)	-2.76 (6.49)
Effect $t + 6$	4.84 (6.47)	-2.48 (6.56)
Average Total Effect	20.08 (24.15)	-12.93 (30.71)
Joint Placebo Test	$p = 0.904$	$p = 0.235$
Observations	4,844	4,844

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Sample restricted to years before 2007 to exclude Great Financial Crisis period. Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Discrete Treatment: Within vs. Across Labor Market Effects

	(1)	(2)
	Auto Binary	NonAuto Binary
Panel A: Within Labor Market (Same CZ)		
Placebo $t - 3$	-1.66 (4.24)	0.47 (3.85)
Placebo $t - 2$	1.57 (3.31)	2.64 (2.92)
Placebo $t - 1$	3.26 (2.58)	2.33 (2.43)
Effect $t + 1$	4.07 (3.34)	-0.16 (2.15)
Effect $t + 2$	7.62*** (2.33)	4.84** (2.16)
Effect $t + 3$	6.12** (2.55)	-0.15 (2.12)
Effect $t + 4$	5.69** (2.47)	-0.39 (2.31)
Effect $t + 5$	2.78 (2.63)	0.87 (2.32)
Effect $t + 6$	4.98** (2.45)	0.13 (2.32)
Average Total Effect	21.25*** (7.78)	3.58 (6.57)
Joint Placebo Test	$p = 0.527$	$p = 0.702$
Observations	9,449	9,449
Panel B: Across Labor Markets (Different CZ)		
Placebo $t - 3$	1.80 (6.96)	-1.47 (6.95)
Placebo $t - 2$	6.78 (5.45)	5.83 (5.13)
Placebo $t - 1$	-3.69 (4.04)	4.46 (4.56)
Effect $t + 1$	0.22 (3.85)	4.23 (3.81)
Effect $t + 2$	2.70 (4.20)	3.69 (4.48)
Effect $t + 3$	-0.04 (4.21)	-1.20 (5.13)
Effect $t + 4$	-2.63 (5.35)	-1.51 (5.33)
Effect $t + 5$	19.74** (8.99)	-3.55 (7.75)
Effect $t + 6$	6.20 (8.34)	-3.15 (8.10)
Average Total Effect	2.95 (11.44)	4.79 (12.15)
Joint Placebo Test	$p = 0.248$	$p = 0.484$
Observations	6,016	6,016

Notes: Coefficients scaled by 100 (discrete treatment, no intensity weighting). Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. Uses binary treatment indicator instead of continuous treatment intensity. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Pooled Sample: Within vs. Across Labor Market Effects

	(1)	(2)
	Auto Binary	NonAuto Binary
Panel A: Within Labor Market (Same CZ)		
Placebo $t - 3$	-2.19 (2.96)	-1.50 (2.91)
Placebo $t - 2$	-0.06 (3.88)	-1.81 (3.53)
Placebo $t - 1$	3.54 (3.14)	0.91 (3.07)
Effect $t + 1$	8.54*** (2.80)	-1.97 (2.63)
Effect $t + 2$	9.53*** (2.69)	4.37* (2.60)
Effect $t + 3$	5.07** (2.16)	1.30 (1.85)
Effect $t + 4$	4.05** (1.89)	0.15 (1.83)
Effect $t + 5$	2.05 (2.03)	2.01 (1.88)
Effect $t + 6$	3.90** (1.87)	0.63 (1.86)
Average Total Effect	20.58*** (6.72)	4.26 (6.20)
Joint Placebo Test	$p = 0.465$	$p = 0.878$
Observations	14,275	14,275
Panel B: Across Labor Markets (Different CZ)		
Placebo $t - 3$	-0.05 (3.59)	1.01 (3.52)
Placebo $t - 2$	2.43 (3.02)	1.12 (2.92)
Placebo $t - 1$	-3.02 (2.57)	1.84 (2.71)
Effect $t + 1$	-4.35* (2.49)	4.57* (2.51)
Effect $t + 2$	-0.98 (2.59)	3.12 (2.88)
Effect $t + 3$	-0.74 (2.62)	0.28 (3.06)
Effect $t + 4$	-1.55 (2.96)	1.96 (3.16)
Effect $t + 5$	7.08 (7.07)	22.87*** (7.22)
Effect $t + 6$	-3.05 (7.21)	9.69 (7.79)
Average Total Effect	-6.44 (7.65)	13.27 (8.52)
Joint Placebo Test	$p = 0.290$	$p = 0.923$
Observations	13,137	13,137

Notes: Coefficients scaled by treatment intensity (within: 0.022×100 ; across: 0.025×100). Pooled sample includes all firms regardless of treatment exclusivity. Panel A shows within-labor-market effects. Panel B shows across-labor-market effects. Standard errors clustered at firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.