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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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# From Shares to Machines: How Common Ownership Drives Automation\*

## Abstract

Does increasing common ownership influence firms' automation strategies? We develop and empirically test a theory indicating that institutional investors' common ownership drives firms that employ workers in the same local labor markets to boost automation-related innovation. First, we present a model integrating task-based production and common ownership, demonstrating that greater ownership overlap drives firms to internalize the impact of their automation decisions on the wage bills of local labor market competitors, leading to more automation and reduced employment. Second, we empirically validate the model's predictions. Based on patent texts, the geographic distribution of firms' labor forces at the establishment level, and exogenous increases in common ownership due to institutional investor mergers, we analyze the effects of rising common ownership on automation innovation within and across labor markets. Our findings reveal that firms experiencing a positive shock to common ownership with labor market rivals exhibit increased automation and decreased employment growth. Conversely, similar ownership shocks do not affect automation innovation if firms do not share local labor markets.

*Keywords: automation, common ownership, local labor markets, market power*

*JEL classification: G23, J23, L22, O32, O33*

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# 1 Introduction

Does institutional investors’ common ownership affect the direction of technological progress, innovation, and automation strategies of their portfolio companies? In this paper, we show that common ownership, i.e., the overlap of the shareholder base of public corporations, leads portfolio firms operating in the same local labor markets to increase their innovation with the intent of automating their production, with important implications for employment outcomes.

Common ownership of publicly traded firms and the automation of tasks previously performed by workers are both rising phenomena in developed economies. [Backus et al. \(2021\)](#) build a measure of common ownership and document that it has tripled among the firms in the S&P 500 between 1980 and 2017. Over the same period, the 10 largest institutional investors have quadrupled their ownership of U.S. stocks and, by the end of 2016, they managed 26.5% of total equity assets ([Ben-David et al., 2016](#)). Economic theory suggests that common ownership of firms competing in the same product market can reduce competition, pushing such markets toward monopolistic outcomes, with consequences for consumer welfare.<sup>1</sup>

On the other hand, growing concerns have emerged regarding the impact of automation technologies on employment, welfare, and inequality. These concerns have been fueled by recent technological advancements, predictions of future developments, and the increasing adoption of automation technologies across various sectors ([Arntz et al., 2016](#); [Frey and Osborne, 2017](#)). Numerous studies have explained the stagnation of median real wages and the decline in wages for less-educated workers from a macroeconomic perspective, attributing these trends to the rise of automation ([Acemoglu and Restrepo, 2018](#); [Moll et al., 2022](#); [Santini, 2024](#)). Additionally, studies focusing on local labor markets have identified negative effects of automation—proxied by robot adoption—on employment and wages ([Acemoglu and Restrepo, 2020](#); [Dauth et al., 2019](#)). However, when using firm-level data, the evidence about the effect of robot adoption on employment and wages is mixed. Some studies find a positive association ([Aghion et al., 2013](#); [Deng et al., 2024](#); [Koch et al., 2021](#)), while others find a negative effect ([Bessen et al., 2023](#); [Bonfiglioli et al., 2024](#)).

Our paper aims to contribute to these two alternative strands of the literature and provide a better understanding of the incentives of firms to automate production. More specifically, we demonstrate the consequences of increasing common ownership of public corporations on

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<sup>1</sup>See, for example, [Macho-Stadler and Verdier \(1991\)](#), [Baker \(2015\)](#), [Posner et al. \(2016\)](#), [Backus et al. \(2021\)](#), [Anton et al. \(2018\)](#). Similarly, [Azar et al. \(2022b\)](#) and [Azar et al. \(2018\)](#) present evidence that common ownership might lead to anti-competitive behavior, higher prices, and lower output in the airline and banking industries.

automation innovation and employment outcomes through a labor market perspective.

In a task-based model of automation, we show that a firm experiencing an increase in their common ownership with rivals in local labor markets will increase the share of automated tasks. This is the case since firms with labor market power internalize the effect of their automation efforts on the wage bill of their commonly-owned rivals incentivizing them to reduce the labor demand.

We empirically test the model’s prediction about the effect of common ownership within local labor markets on automation. To address potential endogeneity issues we use mergers between institutional investors as quasi-natural experiments to exploit exogenous changes in common ownership. As it has been argued in previous literature (He and Huang, 2017a; Lewellen and Lowry, 2021), mergers increase common ownership and are unlikely motivated by policies or performance of individual portfolio firms.

Since firms experience increases in common ownership due to mergers of institutional investors often several times throughout our sample, we apply the state-of-the-art *difference-in-differences* (DID) methods developed by De Chaisemartin and d’Haultfoeuille (2024). Additionally, we create a continuous treatment framework for common ownership since mergers of institutional investors affect firms heterogeneously. Moreover, in this setup, establishment-level information on the distribution of a firm’s labor force allows us to disentangle the causal effects of common ownership on our outcome variables, separately for scenarios with and without labor-market rivalry between portfolio firms. Therefore, this provides compelling evidence that our proposed mechanism is indeed in effect: common ownership increases automation if and only if firms interact in local labor markets.

To measure automation, we apply the classification of patents into automation and non-automation patents proposed by Mann and Püttmann (2021). As discussed by the authors, this approach outperforms those suggested in earlier studies that depend on indirect indicators like the proportion of routine tasks in job descriptions (Autor and Dorn, 2013; Autor et al., 2003; Goos and Manning, 2007), or on limited measures of automation such as expenditure on computer capital (Akerman et al., 2015; Beaudry et al., 2010; Michaels et al., 2014), or investment in robotics (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). Furthermore, applying the Mann and Püttmann (2021) classification, Danzer et al. (2024) show that positive shocks to labor supply due to immigration lead firms to reduce automation innovation. At the same time, the effect on non-automation innovation is nil.<sup>2</sup> This underlines that patents classified as automation innovation reflect firms’ incentives to invest in labor-saving technologies.

We find that firms that experience an increase in common ownership with other firms

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<sup>2</sup>See also Terry et al. (2024) who find a positive impact of immigration on innovation in general.

operating in the same local labor market (i.e., in at least one shared commuting zone) increase patent output related to automation technologies. Simultaneously, we document a decrease in employment growth for these firms. In contrast, the effect of common ownership of firms operating in distinct labor markets on firms’ automation innovation is not statistically significant. Hence, our empirical results suggest, that common ownership by institutional investors among labor-market competitors steers the direction of technological progress into more automation-related innovation, consistent with our theoretical model. Our paper sheds light on the relationship between corporate governance, labor-market competition, and automation.

A battery of tests is conducted to ensure the robustness of our results. First, we use alternative measures of the automation content of firms’ innovation output, weighting patents by their truncation-adjusted citation counts ([Atanassov, 2013](#); [Hall et al., 2001](#)). Using these innovation measures, we corroborate our result that common ownership between labor market rivals increases innovation output related to automation, while non-automation innovation output is not affected. Second, we show that our results are robust to sample selection, pooling our two treatment setups: mergers of institutional investors that increase common ownership within and across local labor markets of a particular firm. Third, [Lewellen and Lowry \(2021\)](#) suggest that the Global Financial Crises could drive the effects attributed to common ownership, as at the same time many firms have been affected by mergers of their institutional owners. Therefore, we corroborate our results using only data up to 2006. Finally, we use a traditional binary treatment variable in our difference-in-differences setting. We find the same qualitative result in all these tests: common ownership between labor market rivals boosts firms’ automation-related innovation output.

Our paper contributes to different strands of the literature in economics and finance. First, it contributes to the debate on the impact of common ownership on firms’ objective function and resulting behavior. The effect of increasing common ownership on product market competition and consumer welfare, as well as its implications for antitrust policy, is investigated by academics in recent years ([Baker, 2015](#); [Posner et al., 2016](#); [Azar et al., 2021](#)). Concerning innovation, [López and Vives \(2019\)](#) show that common ownership may increase R&D investments if it leads firms to internalize the positive externalities of technology spillovers on product market rivals, and [Anton et al. \(2018\)](#) present evidence that common ownership on the firm-pair level might have positive or negative effects on innovation depending on the relative degrees of technology spillovers and product market rivalry between the firms ([Bloom et al., 2013](#)). Finally, [Hutschenreiter \(2023\)](#) shows that common ownership leads to higher technology diffusion across portfolio firms. We contribute to this literature by investigating how common ownership affects another dimension



of firms’ innovation strategy, namely the automation content of their innovation output. We further document a labor-market channel and a firm-level reduction in employment growth due to common ownership.

Another pertinent line of research closely related to our paper lies in the intersection of common ownership, labor market dynamics, and automation. [Azar and Vives \(2019, 2021\)](#) study the effects of common ownership on income shares of production factors in a general equilibrium model, but do not consider automation. [Azar et al. \(2022a\)](#) study the effect of common ownership concentration on local labor-market outcomes and [Azar et al. \(2023\)](#) examine the relationship between monopsony power and automation adoption. We contribute to this literature by presenting firm-level evidence on the relationship between common ownership and the automation-related outcome of innovation strategies. Furthermore, our unique estimation strategy allows us to identify the mechanism behind this relationship: labor-market rivalry is a necessary condition for common ownership to spur investment in automation innovation. That is, we can disentangle the effect of common ownership on our outcome variables for firms operating within and across local labor markets. Furthermore, using the setup of institutional mergers as proposed by [Lewellen and Lowry \(2021\)](#) allows us to present causal estimates applying state-of-the-art dynamic difference-in-difference methodology ([De Chaisemartin and d’Haultfoeuille, 2024](#)).

Finally, our paper is related to research on the impact of automation on wages and employment. Initiated by the seminal research of [Acemoglu and Restrepo \(2020\)](#) for the U.S. and followed by [Dauth et al. \(2019\)](#) for Germany,<sup>3</sup> both studies find negative effects of robot adoption on employment and wages using a local labor market approach. Afterward, the literature transitioned to utilizing firm-level data. This later development presents the challenge of establishing causality by identifying credible exogenous variations. Studies by [Bonfiglioli et al. \(2024\)](#), [Bessen et al. \(2023\)](#), and [Aghion et al. \(2020\)](#) have addressed this issue. The first two papers report negative employment effects, while the third finds a positive effect, arguably due to the different automation proxy used—specifically, investment in industrial equipment—which is likely more complementary to labor. Finally, several studies examine the firm-level outcomes following the adoption of robots. [Deng et al. \(2024\)](#) for Germany, [Koch et al. \(2021\)](#) for Spain, and [Acemoglu et al. \(2020a\)](#) for France all find that employment *increases* in firms after the adoption of industrial robots. We contribute to the literature by identifying an additional mechanism that leads firms to increase their automation effort. That is, we show that a part of the surge in firms’ investments in automation

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<sup>3</sup>In the German context, [Dauth et al. \(2019\)](#) find that robot adoption decreases employment in the manufacturing sector while increasing it in the service sector, keeping aggregate employment unaffected. This mechanism has been formalized by [Hutschenreiter et al. \(2022\)](#).



technologies is the result of common ownership among local labor-market rivals. Common 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. \(2020b\)](#).

The structure of the paper is as follows. 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, along with reporting the results. Finally, Section 4 offers concluding remarks.

## 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).

### 2.1 The model

Consider an economy with  $J$  firms. We call one of these, firm  $f$ , the focal firm, and analyze its automation strategy. The firms operate their production processes in a set of local labor markets  $\mathbf{C}$ , which we interpret as the collection of commuting zones.<sup>4</sup> Thus, a firm  $j$  executes its production in a set  $\mathbf{C}_j \subset \mathbf{C}$ . We say that a firm  $j$  has local labor-market (LLM) overlap with the focal firm  $f$  if both employ production plants in some local labor market at the same time, i.e., there exists some location  $c \in \mathbf{C}_f \cap \mathbf{C}_j$ .

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  $\mathbf{R}_f$ , such that a firm  $j \in \mathbf{R}_f$  has LLM overlap with firm  $f$ , and the set  $\mathbf{N}_f$ , such that  $j' \in \mathbf{N}_f$  implies that  $\mathbf{C}_f \cap \mathbf{C}_{j'} = \emptyset$ . Moreover, we define  $\mathbf{R}_f^c \equiv \{j | j \in \mathbf{R}_f, c \in \mathbf{C}_j\}$ , the set of all firms  $j \neq f$  that operate a plant in a location  $c \in \mathbf{C}_f$  in which firm  $f$  is also present.

We assume that firm  $f$  has some degree of *labor market power* in the local labor markets  $c \in \mathbf{C}_f$  in which it is present. 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  $\partial w_j^c / \partial L_f^c = \rho_{jf}^c > 0$

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<sup>4</sup>To match our empirical analysis, we consider the geographic distribution of firms’ production plants as exogenous.

for all  $j \in \mathbf{R}_f \cup \{f\}$ ,  $c \in \mathbf{C}_f \cap \mathbf{C}_j$ , where  $L_f^c$  is firm  $f$ 's labor demand in  $c$  and  $w_j^c$  the wage firm  $j$  has to pay in order to employ a given amount of labor in the same location. For instance, if firm  $f$  increases its labor demand in some of its plants it increases the outside option of workers in the locations in which these plants operate. Thus, we call the firms in  $\mathbf{R}_f$  firm  $f$ 's labor-market rivals.

We abstract from wage spillover effects between LLMs, i.e.,  $\partial w_j^{c'}/\partial L_j^c = 0$ , for all  $j, j' = 1, 2, \dots, J$  and all  $c, c' \in \mathbf{C}$ ,  $c \neq c'$ . In particular, this implies that firm  $f$  cannot affect the wages that other firms pay in locations  $c' \notin \mathbf{C}_f$ , in which it does not operate, i.e.,  $\partial w_j^{c'}/\partial L_f^c = 0$ , for all  $c \in \mathbf{C}_f$ ,  $j \in \mathbf{N}_f$ . Hence, there is no labor-market rivalry between firms in  $\mathbf{N}_f$  and  $f$ .

For simplicity, we abstract from product market competition and all firms are price takers in the capital market.<sup>5</sup> We can think about the firms  $j = 1, 2, \dots, J$  as multi-product firms producing different goods  $Y_j^c$  in each establishment 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. They take the rental rate  $r$  of capital  $K$  as given.

There exists a collection of institutional investors who may own shares in the firms. Drawing on the literature, which suggests that good corporate governance induces management to maximize a weighted average of investors' cash flows from their portfolio, we posit that firm  $f$ 's objective function, under common ownership, internalizes the impacts 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

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

where  $\pi_j$  is the profit function of firm  $j$  and  $\lambda_{fj} \geq 0$  is the profit weight firm  $f$  puts on firm  $j$ 's profits. The parameter  $\lambda_{fj}$  is a function of the cashflow rights of firm  $f$ 's investors to the profits of firms  $f$  and  $j$ . In particular,  $\lambda_{fj}$  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  $\lambda_{fj}$  in our analysis.

At each location  $c \in \mathbf{C}_f$ , focal firm  $f$  has access to a technology that by performing a continuum of distinct tasks  $x^c \in \mathbf{X}^c = [0, 1]$  produces output  $Y_f^c$ . The final output of firm  $f$

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<sup>5</sup>For 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.

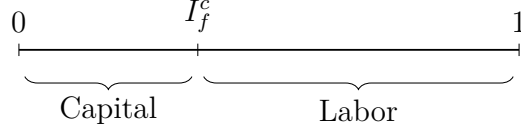


Figure 1: Allocation of capital and labor to tasks over the set  $\mathbf{X}^c$  in firm  $f$ 's plant in location  $c$ .

in location  $c$  is given by the production function

$$Y_f^c = \exp \left( \int_{\mathbf{X}^c} \ln [y_f(x^c)] dx^c \right)^\nu \quad (2)$$

where  $y_f(x)$  is the quantity of the task (indexed by  $x^c$ ) employed in production, and  $\nu < 1$  is the degree of return to scale. Each amount of task  $x^c \in \mathbf{X}^c$  performed in a location  $c \in \mathbf{C}_f$  is produced according to the following intermediary production function,

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

in which quantities of machines  $m_f(x^c)$  and labor  $\ell_f(x^c)$  are perfect substitutes, and  $\gamma_m^c(x)$  and  $\gamma_\ell^c(x)$  are the productivity schedules of capital and labor over the task measure. Without loss of generality, we assume that at each production site of firm  $f$  in the locations,  $c \in \mathbf{C}_f$ , the productivity schedules are continuously differentiable over each set  $\mathbf{X}^c$  and this set is ordered in such a way that the comparative advantage of producing a task with labor strictly increases in  $x^c$ , i.e.,  $d/dx^c(\gamma_\ell^c(x^c)/\gamma_m^c(x^c)) > 0$  for all  $x^c \in \mathbf{X}^c$ .

Then, firm  $f$  chooses its inputs, such that each set  $\mathbf{X}^c$  of tasks is divided into two regions: the tasks produced with capital and the tasks performed by labor, as shown in Figure 1. The threshold that separates the two sets is  $I_f^c \in \mathbf{X}^c$ .

Then,  $I_f^c \in [0, 1]$  is the degree of automation of the plant in location  $c$ . Thus, firm  $f$ 's average degree of automation is given by

$$I_f \equiv \frac{1}{|\mathbf{C}_f|} \sum_{\mathbf{C}_f} I_f^c \quad (4)$$

To maximize its objective function firm  $f$  solves the following program.

$$\mathcal{P}_f \left\{ \begin{array}{ll} \max_{\Omega_f} & \sum_{\mathbf{C}_f} (p_f^c Y_f^c - r K_f^c - w_f^c L_f^c) + \sum_{j \neq f} \lambda_{fj} \left\{ \sum_{\mathbf{C}_j} (p_j^c Y_j^c - r K_j^c - w_j^c L_j^c) \right\}, \\ & \text{subject to} \\ & Y_f^c = \exp \left( \int_{\mathbf{X}^c} \ln [y_f(x^c)] dx^c \right)^\nu \\ & y_f(x^c) = \gamma_m^c(x^c) m_f(x^c) + \gamma_\ell^c(x^c) \ell_f(x^c) \\ & K_f^c = \int_{\mathbf{X}^c} m_f(x^c) dx^c \\ & L_f^c = \int_{\mathbf{X}^c} \ell_f(x^c) dx^c, \end{array} \right.$$

where  $\Omega_f = \{Y_f^c, K_f^c, L_f^c, y_f(x^c), m_f(x^c), \ell_f(x^c)\}$  and we define  $L_f \equiv \sum_{\mathbf{C}_f} L_f^c$  as its total labor input. Moreover,  $K_f \equiv \sum_{\mathbf{C}_f} K_f^c$  is the amount of capital it employs.

We are interested in the relationship between the degree of common ownership,  $\lambda_{fj}$ , with some other firm  $j$  in the economy and the optimal level of automation  $I_f$ . We state our first result in the following proposition:

**Proposition 1.** *If common ownership, i.e., the profit weight  $\lambda_{fj}$ , of firm  $f$  with respect to some labor-market rival firm  $j \in \mathbf{R}_f$  increases, then the optimal level of automation  $I_f$  of firm  $f$  increases.*

*Proof.* See the theoretical appendix A. □

Intuitively, as common ownership with a labor-market rival increases, the extent to which firm  $f$  internalizes the profit of this firm also increases. The only way in which firm  $f$  can affect the profit of firm  $j \in \mathbf{R}_f$  in our model is by decreasing its wage bill and, to achieve this it decreases the level of labor input in locations  $c \in \mathbf{C}_f \cap \mathbf{C}_j$ . That is firm  $f$  trades off the cost of reducing its labor demand with the benefit of decreasing firm  $j$ 's wage bill, which it now internalizes to a higher degree. This implies a reduction in labor input by firm  $f$  in these plants. To mitigate the cost of this reduction, it chooses a higher degree of automation  $I_f^c$  in plants  $c \in \mathbf{C}_f \cap \mathbf{C}_j$ . In other words, an increase in common ownership increases the *internalized* marginal factor cost of labor for firm  $f$ , i.e.,  $(\partial w_f^c / \partial L_f^c) L_f^c + w_f^c + \lambda_{fj} (\partial w_j^c / \partial L_f^c) L_j^c$  in locations  $c \in \mathbf{C}_f \cap \mathbf{C}_j$ , that accounts for the cost of a marginal increase in labor demand by firm  $f$  on firm  $j$ 's profits. Therefore, in each affected location the incentives to substitute labor with capital increase, increasing the set of tasks  $[0, I_f^c]$  produced with capital by shifting  $I_f^c$  to a higher indexed task  $x^c \in \mathbf{X}^c$ . The degree of automation  $I_f^c$  of the plants in  $c \in \mathbf{C}_f \cap \mathbf{C}_j$  increases, leading to a higher degree of automation  $I_f$  of firm  $f$ . Hence, if the firm experiences a positive shock to common ownership with one of its labor-market rivals and it is producing at the ex-ante optimal level of automation, we expect that this shock causes the firm to increase its effort to automate additional tasks.

We have seen that common ownership in our model causes an increase in the optimal degree of automation if and only if a firm can affect the wage bill of the other firm through its labor demand. The next result follows immediately.

**Corollary 1.** *Common Ownership between firm  $f$  and a firm  $j' \in \mathbf{N}_f$  does not affect firm  $f$ 's optimal degree of automation  $I_f$ .*

*Proof.* The result immediately follows from the fact that firm  $f$  cannot influence the wage bill of firm  $j'$ . Thus, the profits of firm  $j'$  do not depend on firm  $f$ 's strategic choices.  $\square$

In the next subsection, we discuss the results derived from the model to develop testable hypotheses.

## 2.2 Hypothesis development

In this section, we translate the theoretical results into testable empirical hypotheses. Drawing on Proposition 1, we have seen that a necessary condition for common ownership to alter firms' strategies regarding automation 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 local labor markets and those that operate in distinct labor markets. To this end, we define labor market rivals using their 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 that are located in at least one shared commuting zone at the same time. Furthermore, we use a classification of patents into automation and non-automation patents based on patent texts to measure the automation content of firms' innovation output. Then, we focus on a positive shock in common ownership of a focal firm with respect to labor market rivals. Given the result in proposition 1, we test the following hypothesis:

**Hypothesis 1.** *An increase in common ownership to local labor market rivals causes the focal firm to increase the automation content of its innovation output.*

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, after such a shock to common ownership occurs, a firm has to adopt its degree of automation by innovating. Furthermore, as Corollary 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:

**Hypothesis 2.** *An increase in common ownership with firms employing labor in different commuting zones does not cause the focal firm to focus more on automation innovation.*

## 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 seven 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. Finally, (vii) we use the Mann and Püttmann’s (2021) classification of the universe of USPTO patents as either automation or non-automation patents. We now explicitly define the variables used in our empirical analysis.

### 3.2 Variables

#### 3.2.1 Common Ownership

To measure common ownership, we follow the recent literature and use the *Cindex* (Lewellen and Lowry, 2021). Common ownership of firm  $j$  at time  $t$  is defined in the following way:

$$Cindex_{jt} = \frac{1}{K} \sum_{k=1}^K \sum_i \beta_{ij} \beta_{ik}, \quad (5)$$

where  $j$  denotes the focal firm,  $i$  indicates investors owning it, and  $k = 1, 2, \dots, K$  indexes the relevant set of firms. Furthermore,  $\beta_{ij}$ ,  $\beta_{ik}$  are the fractions of outstanding shares of firms  $j$  and  $k$ , respectively, that investor  $i$  owns as of the calendar year-end. Because we want to study the effect of changes in common ownership of a focal firm with its local labor market (LLM) rivals, we construct our main measure of common ownership  $CindexLLM_{jt}$ , such that it only takes into account these  $K_{LLM_j}$  firms that have labor-market overlap with firm  $j$ , that is they operate in at least one commuting zone in which the focal firm  $j$  is present. Analogously, we compute  $CindexALL_{jt}$ , for which the relevant set of firms is  $K_{ALL}$ , i.e., all other firms.

### 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 for automation or not.<sup>6</sup> Table 1 gives examples taken from the original paper of both innovation types.

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

Table 1: This table shows examples of patents’ classification into automation or non-automation patents. Source: [Mann and Püttmann \(2021\)](#).

In summary, the authors train a naïve Bayes classifier. They define two classes, automation and non-automation. They first manually classify 560 patents into both classes and define, through the mutual information criterion, a set of words informative about each class. Words that identify that a patent is an automation device are *automat*, *output*, *execute*, *inform*, *input*, and *detect*.<sup>7</sup> The algorithm then uses the occurrence of these words to

<sup>6</sup>The 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.

<sup>7</sup>These words are stemmed first, to capture variations of the same word, for example, automation, automate, and automatic all stem from the word automat.



calculate a probability that the patent belongs to 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 probability of a false positive (type-1) and a false negative (type-2) are 21 and 17 percent, respectively. For the out-of-sample testing, performance declines slightly. However, the corresponding statistics for true positives, false positives, and false negatives are 77%, 23%, and 22%.

Using a broad definition of innovation and the machine learning method allows us to measure innovation for a large sample of firms, across industries and time. While errors in the classification process 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.

Given this patent-level classification, we construct different measures of innovation output on the firm-year level that allow us to evaluate changes in the automation strategy of firms. The first and main measure gauges the automation content of firms' innovation output, i.e.,

$$AutoRatio = \ln \left[ \frac{1 + \text{Number of automation Patents}}{1 + \text{Number of non-automation Patents}} \right] \quad (6)$$

*AutoRatio* measures the extent to which a firm focuses on innovation for automation vs. inventions unrelated to automation. Thus, it allows us to observe changes in the automation strategies of firms on the intensive margin.

The second measure, *AutoDummy*, is an indicator variable that takes the value one if a firm in a given year applies for a patent that was eventually granted and is classified as an automation patent according to [Mann and Püttmann \(2021\)](#), and zero otherwise. We use this measure to assess changes in the propensity of firms to invest in automation technologies.

We also use patent counts to assess the effect of common ownership on automation and non-automation innovation separately to study whether changes in *AutoRatio* result from increases (decreases) in the number of automation (non-automation) patents, respectively.  $\ln Auto$  and  $\ln NonAuto$  are the natural logarithms of (one plus) the number of automation and non-automation patents, respectively.

### 3.2.3 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,

$$EmpGrowth_t = \frac{Employees_t - Employees_{t-1}}{Employees_{t-1}}, \quad (7)$$

where  $Employees_t$  is the number of employees (in thousands) of a firm in year  $t$ . Moreover, we compute the indicator variable  $EmpIncrease$  that takes the value one if a firm experiences positive employment growth, and is zero otherwise.

### 3.2.4 Treatment variables

Following the recent literature on common ownership and the estimation of its causal effects (Lewellen and Lowry, 2021), we use exogenous changes in common ownership due to the mergers of institutional investors. We use the information on 53 institutional mergers from 1990 to 2010 and, in particular, their announcement dates and the merging parties' ownership in the universe of publicly traded companies in the quarter before the announcement date to define a set of continuous and discrete treatment variables.<sup>8</sup>

*Treated by merger*—First, we define a set of firm-years in our panel that is treated by a merger of institutional investors similar to He and Huang (2017b) and Lewellen and Lowry (2021). We call this set  $\mathbf{T}$ . The firms in  $\mathbf{T}$  are treated in the sense that the merger is likely to increase their shareholder overlap with other firms. For this reason, we require that (i) for a firm (say firm 1, or the focal firm) to be treated by a merger, one of the merging investors (say investor A) holds at least 1% of outstanding shares of this firm before the merger (i.e., as of the quarter preceding the quarter of the merger announcement date). (ii) There must be at least one other firm (say firm 2) such that the other merging investor (say, B) owns 1% (again as of the quarter before the merger announcement) of this second firm. Furthermore, (iii) for this pair (firm 1, firm 2), neither of the two investors (A or B) can hold more than 1% in both firms in the quarter before the merger announcement, such that the merger is likely to lead to a new common shareholder (the merged institution) that holds at least 1% in both companies but did not do so before the merger. The firms satisfying these three criteria are likely to experience an increase in common ownership with some other firm in the economy due to the merger.<sup>9</sup>

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<sup>8</sup>We 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 stay qualitatively the same.

<sup>9</sup>At the same time, these firms are not likely to experience changes in their shareholder composition and concentration, since only one of the merging parties (A) holds more than 1% of outstanding shares, while we require the other investor (B) to hold less than 1% or none of the shares. This is crucial since Guo et al. (2024) have shown that mergers of institutional investors that both hold significant shares in one firm increase

*Treatment within Commuting Zones*—Second, we define a subset  $\mathbf{T}_{LLM} \subset \mathbf{T}$  of firm-years identified as treated by a merger above to construct our main treatment variable. We are interested in exploiting exogenous changes to common ownership between firms that operate in the same local labor markets. To do so, we modify criterion (ii) above such that we require the existence of a firm 2 that operates in at least one commuting zone in which also focal firm 1 operates, i.e., they have local labor market (LLM) overlap. Thus, firms treated in this sense likely experience positive changes to their common ownership with a local labor market peer. Hence, we expect that their  $Cindex_{LLM}$ , as defined above, increases.

Therefore, for those firms that satisfy these three criteria with LLM overlap our first discrete treatment variable,  $Treat_{LLM}$  takes the value one in the year of the quarter that immediately precedes the merger announcement and is zero otherwise.

Since firms may be treated to a different extent depending on the size of the holdings of the merging parties, we also construct a continuous treatment variable. This variable corresponds to the implied change in the  $Cindex$  of the focal firm to the other. To this end, we can compute the firm-pair level  $Cindex_{12} = \sum_i \beta_{i1}\beta_{i2}$  for a firm-pair (the focal firm 1 and its LLM rival, firm 2) at the time of the quarter preceding the merger announcement. We also can compute the counterfactual

$$Cindex_{12}^{merged_{AB}} = (\beta_{A1} + \beta_{B1})(\beta_{A2} + \beta_{B2}) + \sum_{i \notin \{A,B\}} \beta_{i1}\beta_{i2}, \quad (8)$$

in which we treat the two investors as having already merged, using the same pre-announcement quarter ownership shares. The difference between the counterfactual and the actual  $Cindex$  is then given by

$$\Delta_{12}^{merged_{AB}} \equiv Cindex_{12}^{merged_{AB}} - Cindex_{12} = \beta_{A1}\beta_{B2} + \beta_{B1}\beta_{A2}, \quad (9)$$

that is the expected change of the firm-pair level  $Cindex$  due to the merger affecting the investors A and B in firms 1 and 2, and the  $\beta_{ik}$  are the corresponding holdings of the investors  $i \in \{A, B\}$  in firm  $k = 1, 2$  as of the quarter before the merger announcement. The firm-level continuous treatment variable,  $ContTreat_{LLM}$ , sums these implied changes for the focal firm over all affected LLM rivals and takes a positive value whenever  $Treat_{LLM}$  takes the value one, and is zero otherwise. Thus,  $ContTreat_{LLM}$  can be interpreted as the treatment dose.

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block holder ownership, which results in changes to firms' innovation strategy and outcomes. Because of the careful construction of our treatment sample and since we also distinguish the effect of treatment by mergers for firms within and across commuting zones, finding differential results, we can confidently conclude that changes in ownership concentration do not drive our results.

*Treatment across Commuting Zones*—Finally, we define the subset of firm-years  $\mathbf{T}_{notLLM} \subset \mathbf{T}$  that was treated by a merger however that do not observe an exogenous increase in their *CindexLLM* with any LLM competitors. Therefore, this subset of firm-years is the complement of the firm-years that experience changes in common ownership with firms within the commuting zones and thus partitions the set  $\mathbf{T}$ , i.e.,  $\mathbf{T}_{notLLM} = \mathbf{T} \setminus \mathbf{T}_{LLM}$ .

The discrete (*TreatnotLLM*) and continuous (*ContTreatnotLLM*) treatment variables are then defined analogously for this subset of firms treated by mergers as their respective counterparts in the previous paragraph. In the main corpus of our paper, we use the continuous treatment variables. However, using the discrete treatment setup we obtain qualitatively consistent results.

### 3.2.5 Control variables

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 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 and we include firms’ total number of employees scaled by total assets *EmptoAssets* (in thousands).

## 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 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 LLM 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

Variable	25th Perc.	Median	Mean	75th Perc.	Std. Dev.	N. of obs.
<b>Ownership:</b>						
<i>CindexLLM</i>	0.001	0.002	0.003	0.004	0.003	17203
<i>CindexALL</i>	0.001	0.002	0.002	0.003	0.002	17203
<i>InstOwn</i>	0.187	0.463	0.460	0.713	0.297	17203
<b>Firm Characteristics:</b>						
<i>R&amp;DtoAssets</i>	0.027	0.076	0.121	0.147	0.206	17203
<i>TotalAssets (in \$1M)</i>	44.187	168.829	2506.583	858.900	11528.576	17203
<i>FirmSize</i>	3.788	5.129	5.348	6.756	2.150	17203
<i>FirmAge (in years)</i>	7.000	13.000	17.349	23.000	13.978	17203
<i>FirmAge</i>	1.946	2.565	2.543	3.135	0.809	17203
<i>PPEtoAssets</i>	0.070	0.141	0.182	0.250	0.149	17203
<i>Employees (in 1K)</i>	0.190	0.654	7.097	3.474	24.613	17203
<i>EmptoAssets</i>	0.002	0.004	0.006	0.007	0.006	17203
<i>EmpGrowth</i>	-0.055	0.039	0.132	0.175	0.999	16299
<i>EmpIncrease</i>	0.000	1.000	0.599	1.000	0.490	16299
<b>Patent output:</b>						
<i>NumPatents</i>	0.000	1.000	26.683	8.000	125.409	17203
<i>NumAutoPatents</i>	0.000	1.000	16.628	4.000	97.091	17203
<i>AutoRatio</i>	0.000	0.000	0.357	0.693	1.123	17203
<i>AutoDummy</i>	0.000	1.000	0.534	1.000	0.499	17203
<i>lnAuto</i>	0.000	0.693	1.055	1.609	1.399	17203
<i>lnNonAuto</i>	0.000	0.000	0.698	0.693	1.318	17203
<b>Treatment:</b>						
<i>TreatLLM</i>	0.000	0.000	0.058	0.000	0.234	17203
<i>ContTreatLLM</i>	0.000	0.000	0.001	0.000	0.010	17203
<i>TreatnotLLM</i>	0.000	0.000	0.022	0.000	0.147	17203
<i>ContTreatnotLLM</i>	0.000	0.000	0.001	0.000	0.005	17203

Table 2: This Table presents descriptive statistics for our sample of patenting firms from 1990 to 2012.

our sample selection process yields an unbalanced panel of 1,558 firms, comprising 17,203 firm-year observations for which none of the variables used in our analysis is missing.

Table 2 reports summary statistics for our sample. The average  $CindexLLM$  is larger than the average  $CindexALL$ , with values of 0.003 and 0.002, respectively. This shows that the average firm has a slightly higher overlap of institutional shareholders with the average firm that operates in the same commuting zones than with the average firm operating in a disjunct set of local labor markets. Paired and unpaired  $t$ -tests reveal that the difference is significant at 1%, showing that common ownership of firms with labor-market overlap seems to be relevant when comparing it with ownership overlap in general. Institutional investors hold 46% of outstanding shares of the average firm in our sample, similar to what was found in other studies for our sample period.<sup>10</sup>

Moreover, the average firm in our sample invests 12.1% of total assets into research and development (R&D) activities.<sup>11</sup> Firms' total assets are around \$2.5B and they are older than 17 years on average. The mean number of Employees is 7 thousand. Firms' ratio of tangible to total assets ( $PPEtoAssets$ ) is 18.2%.

On average, firms produce around 27 patents per year of which 17 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 53.4%.

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

The set  $\mathbf{T}$  of firm-years that we define as treated by a merger (as described in Section 3.2.4) consists of 1,380 firm-years corresponding to 802 firms. Of these firm-years 998 are in the set  $\mathbf{T}_{LLM}$ , comprising 585 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  $\mathbf{T}_{notLLM}$ , 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 382 firm-years in this set, consisting of 361 companies.

In pooled regressions in the Appendix (Section C.2) we use all 998 event firm-years to estimate the effect of  $ContTreatLLM$  in a robustness check. However, for reasons described in the following section, in our baseline estimation, we exclude observations of firms that are treated at least once during our sample period by the treatment  $ContTreatnotLLM$ , when estimating the effect of  $ContTreatLLM$ . This leaves us with a sample of 734 observations in

<sup>10</sup>For 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.

<sup>11</sup>It 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.

Set of firms:	<b>T<sub>LLM</sub></b>			<b>T<sub>notLLM</sub></b>			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	734	1.000	0.000	220	0.000
<i>ContTreat (cont.)</i>	0.021	0.038	734	0.025	0.023	220	-0.004

Table 3: This Table compares the average dose treatment within each treatment across the two treatment samples, **T<sub>LLM</sub>** and **T<sub>LLM</sub>**, and the Control firm years.

**T<sub>LLM</sub>**. To estimate the effect of *ContTreatnotLLM* we proceed analogously (excluding all observations of firms that are treated at least once by *ContTreatLLM*). This results in 220 observations in the set **T<sub>notLLM</sub>**.

Next, we compare the average treatment doses among the two sets of treated firm-years. That is, we compare the mean doses of treatment within each treatment sample of the two subsets of firms affected by mergers. For our baseline samples, the average of the 734 firms treated by mergers that likely increase common ownership with labor-market rivals is 0.021.<sup>12</sup>

The average treatment dose of the 220 firms affected by an institutional merger is almost 20% larger, amounting to 0.025.<sup>13</sup> The average dose of treatment for firms in **T<sub>notLLM</sub>** is higher compared to their counterparts in **T<sub>LLM</sub>** to their labor-market rivals. 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. We start by testing 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 (*CindexLLM*) and the automation strategy of firms (*AutoRatio*) on the firm level. To this end, we estimate the model in equation (10).

$$AutoRatio_{j(t+\tau)} = \beta_0 + \beta_1 CindexLLM_{jt} + \gamma X_{jt} + \alpha_j + \delta_{st} + \epsilon_{jt} \quad (10)$$

<sup>12</sup>To help the understanding of this number, we can provide the following example that corresponds to an average treatment dose of 0.021. Assume that the focal firm has a 5% blockholder (say, investor A) that merges with another institutional investor (say, B). In the symmetric case, this other investor would hold 5% in 8.4 other firms in which A is not invested, but these firms are active in a subset of commuting zones in which the focal firm operates.

<sup>13</sup>This average treatment dose corresponds to the merger of a 5% blockholder of the focal firm with an investor that holds 5% if 10 firms without labor-market overlap to the focal firm.



$AutoRatio_{j(t+\tau)}$  is the  $\tau$ th lead of our main 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 case of success. Therefore, we consider  $\tau = 1, 2, 3, \dots, 6$  in the OLS panel regression.  $CindexLLM_{jt}$  is the common ownership measure at the firm-year level defined in section 3.2.1. Further, we include  $X$ , the control variables discussed previously, and a set of firm and industry (s)  $\times$  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.

As mentioned, estimating two-way fixed effect (TWFE) models in the presence of dynamic effects may lead to biased estimates. [Sun and Abraham \(2020\)](#) show that in cases such as ours, where firms are treated at different times, estimating lead or lagged models can produce biased effects, affecting model conclusions but also the researcher’s ability to trust pre-trend analysis. They show that dynamic effects in TWFE models can be expressed as the linear combination of cohort-specific effects across time. For example, we cannot disentangle the contemporaneous effect of an increase in common ownership from long-term changes to the strategic direction of the firm. We therefore employ the state-of-the-art event study DID model developed in [De Chaisemartin and d’Haultfoeulle \(2024\)](#) which allows us to estimate dynamic effects, under a set of more reasonable assumptions.

To derive exogenous variation in the *Cindex* we use mergers between institutional investors as in [He and Huang \(2017b\)](#) and [Lewellen and Lowry \(2021\)](#), applying the set of continuous treatment variables defined in Section 3.2.4. As we discussed there, if institutional investors merge, they combine their portfolios, and firm-level common ownership likely increases for their portfolio firms, as we subsequently show in the data.

This identification strategy requires that financial institutions’ mergers are not driven by the specific characteristics of the firms in which these institutions invest, in particular their automation strategies. There are several reasons why this is plausible. As [He and Huang \(2017b\)](#) show, about 60% of mergers result from consolidations in the banking sector, caused by fundamental changes in the regulation of financial institutions. This led to a wave of mergers of these institutions and their asset management arms. Given the scope of the regulations and the size of the financial institutions involved, it is unlikely that the reasons for their mergers are due to individual portfolio companies’ characteristics. Second, [Jayaraman et al. \(2002\)](#) suggest that the mergers of pure asset management institutions, i.e., the remaining 40% of the mergers, are due to strategic reasons such as exploiting economies of scale and gaining market share. Thus, these mergers are also unrelated to portfolio

firm characteristics such as innovativeness, automation, or the geographic distribution of individual firms' plants.

Having established the validity of our shock to common ownership, we describe the procedure we use to test our empirical hypotheses. Regarding Hypothesis 1, we are interested in changes of common ownership of a firm with respect to local labor market (LLM) rivals. Therefore, we use the continuous treatment variable *ContTreatLLM*, which accounts for the firms' exogenous change in common ownership with LLM rivals implied by the merger. We use this treatment variable in the estimation method presented by [De Chaisemartin and d'Haultfoeuille \(2024\)](#), which is flexible to the usage of continuous treatments and our setup, in which firms may be treated several times during our sample period. As our main outcome of interest is the automation strategy of firms, we use the two automation measures, *AutoRatio* and *AutoDummy*, as the dependent variables in this experiment. Thus, we estimate the dynamic effects of treatment to LLM common ownership on the automation strategy of firms, using the universe of not(-yet) treated firms as controls. In this model, we also employ the firm characteristics described in Section 3.2.5 as control variables.

Next, regarding Hypothesis 2 in which we want to see the effects of common ownership of a focal firm concerning others, which are not natural labor market rivals of the focal firm, we apply our continuous treatment variable *ContTreatnotLLM*, analogously. Thus, we test if a firm that experiences a positive shock to common ownership, however only with regard to firms with which it does not compete for workers, increases the automation content of its innovation output in the same way, as we expect for those within local labor markets.

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 exclude firms that have ever been treated by one of these treatments, when estimating the effect of the other. For instance, when estimating the effect of *ContTreatLLM*, we exclude all companies from the sample for which there is any firm year in which *ContTreatnotLLM* takes a positive value, and vice versa. For robustness, we have also estimated the effects in pooled samples. 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. There are for instance 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 up to 2006, before the onset of the crisis. All our results

stay qualitatively consistent with our baseline analysis, therefore reducing this concern. We report the results in the appendix (Section C.3).

Another critique we address concerns the use of continuous treatment measures, instead of binary treatment variables. The key assumption we have to make is that the ownership shares as of the quarter before the announcement date of merging investors are exogenous. To address the concern that this might introduce some sort of endogeneity, we have estimated our model also using the discrete treatment variables (*TreatLLM* and *TreatnotLLM*) and report results (Section C.4 in the appendix) that are consistent with our estimations using continuous treatments.

Finally, we also have computed alternative measures of automation innovation based on citation counts of patents. The results reported in Section C.1 in the appendix are also consistent with our baseline strategy.

## 3.5 Empirical Results

In this section, we present the results of our empirical analysis.

### 3.5.1 Common Ownership of Labor Market Rivals and Automation Innovation

*OLS Results*—We first estimate model (10). The results are shown in Table 4 in the Appendix (Section B). As the results indicate, firms show on average a higher share of innovation output related to automation (relative to other innovations) one to five years into the future when they have higher common ownership to LLM rivals. 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. Therefore, we now turn to the dynamic Difference-in-Difference model using the exogenous changes in common ownership.

*Relevance of Treatment*—To test Hypothesis 1 using the DID model, we first show that mergers between institutional investors lead to an increase in the average common ownership with LLM rivals, using the continuous treatment *ContTreatLLM* and the *CindexLLM* as the dependent variable. [Lewellen and Lowry \(2021\)](#) show that institutional mergers lead to an increase of common ownership on the firm-pair level. 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 an LLM rival on the firm-pair level is not compensated by other changes in common ownership with other LLM rivals, since our

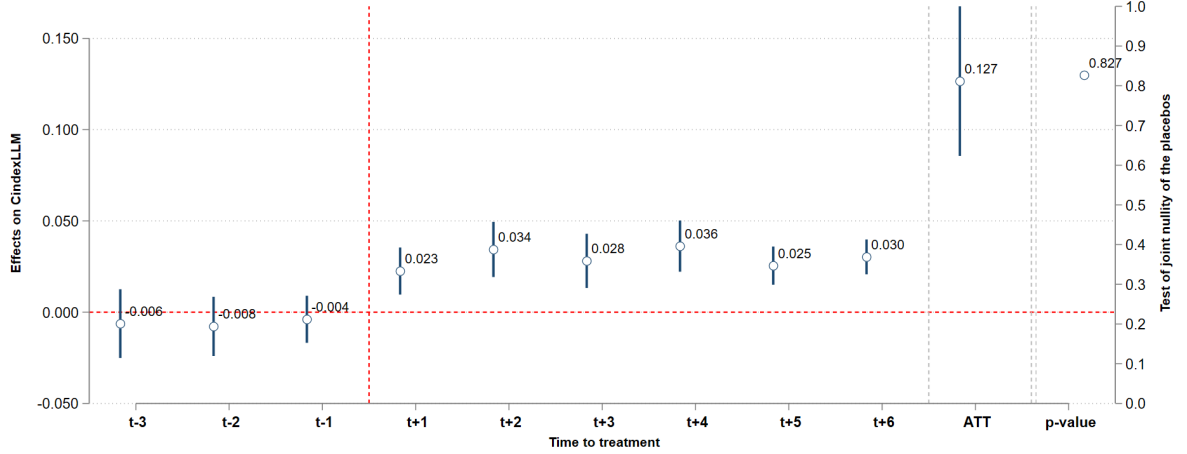


Figure 2: The dynamic effect of being treated by an institutional merger that likely increases common ownership with LLM rivals (*ContTreatLLM*) on the raw firm-level common ownership regarding LLM rivals (*CindexLLM*).

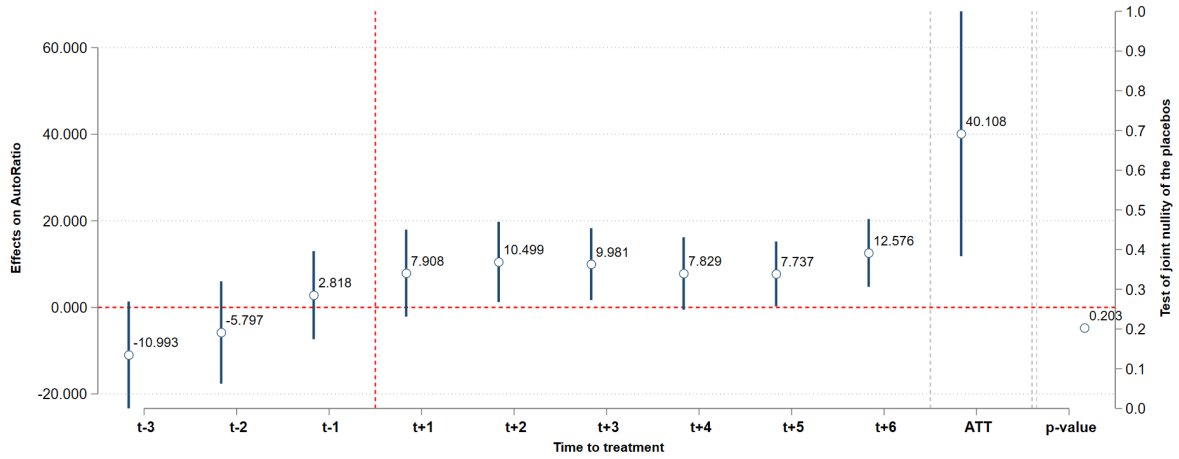
outcome variables are defined on the firm level.

Figure 2 indeed shows a jump in the average *CindexLLM* following treatment in year 0. The positive shock to common ownership amounts to 0.023 percentage points in the average merger event and is persistent during the six years following treatment.<sup>14</sup> The pre-treatment period effects are not significant and the p-value of joint nullity of the placebos is 0.827, which indicates that the parallel-trends assumption is satisfied. Therefore, we can conclude that treated firms experience a common ownership increase with other firms in the same local labor markets.

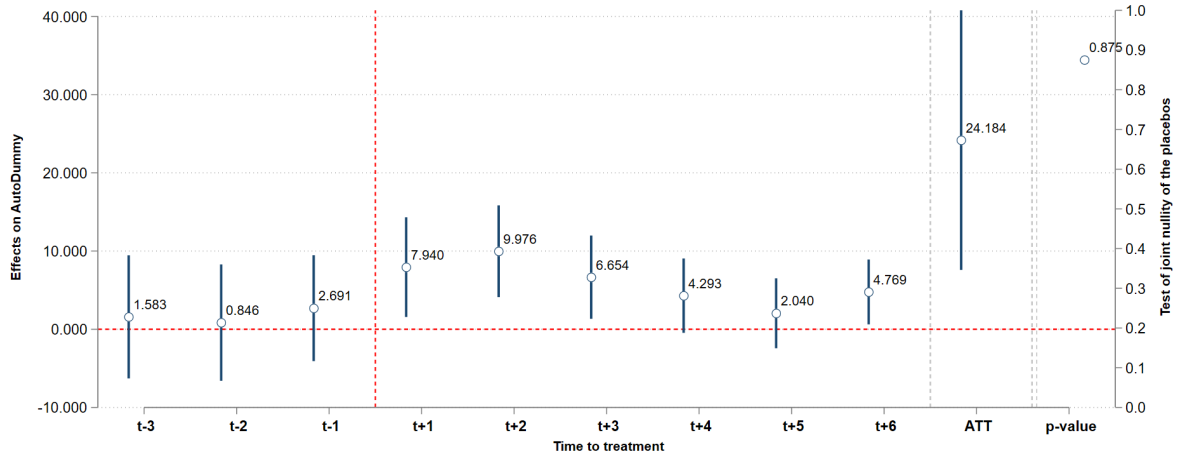
*Automation Strategy*—We now turn to our main outcome variables to test Hypothesis 1. The principal model uses *AutoRatio* as the dependent variable to test whether the firm changes its innovation strategy to become more automation-focused, controlling for a potential change in total innovation. We also use the automation indicator variable, *AutoDummy* to test if the exogenous changes to common ownership affect firms’ propensity to invest in automation.

Figure 3 shows that an increase in common ownership with local labor market rivals due to a merger leads to a significant increase in the automation content of innovation for the treated firms in  $\mathbf{T}_{LLM}$  over the six years following treatment. This increase is also economically significant, as it corresponds to a change of 40.1% for the average treated firm. In the discrete treatment setup, the resulting change in the ratio of automation to non-automation patents reported in the Appendix (Section C.4) is 44%. On a yearly basis, we

<sup>14</sup>As defined in Section 3.2.1, the dependent variable is the average ownership overlap of the focal firm with all its labor market rivals.



(a) Using the continuous measure *AutoRatio*



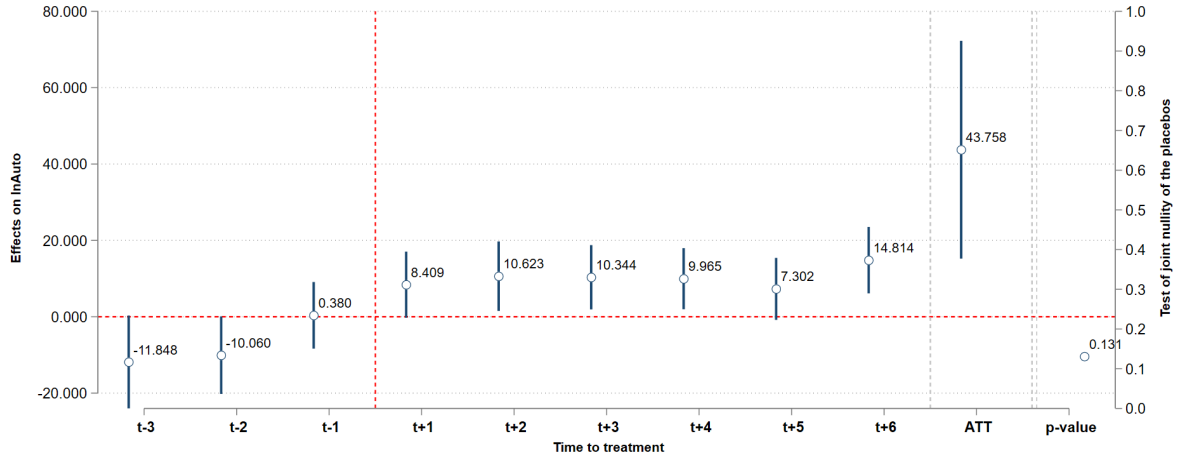
(b) Using the binary measure *AutoDummy*

Figure 3: This Figure shows the dynamic effects of within-LLM increases to common ownership (*ContTreatLLM*) on the automation strategy of firms.

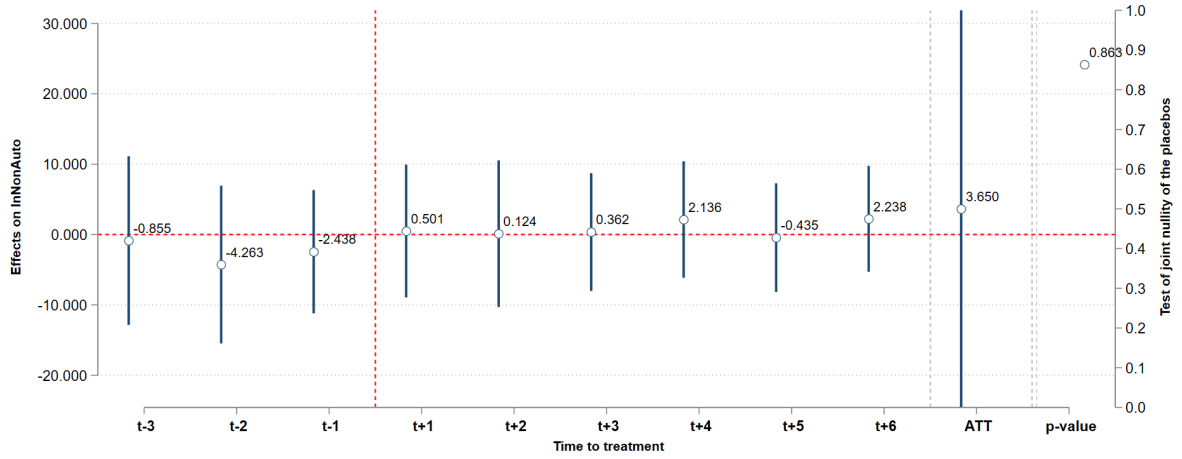
see that the automation content of innovation increases significantly by about 10%, two and three years after the event.

The propensity of firms to produce automation patents significantly increases by 6.6 to almost 10 percentage points in the first three years after the average merger event, as indicated in Panel (b) of Figure 3. This corresponds to a 12.4% to 18.7% increase in the probability of patenting an automation innovation over the unconditional mean.

Next, we use the simple patent count variables, *lnAuto* and *lnNonAuto* to examine individually which type of patenting drives our effects. The indicator variable *AutoDummy* suggests that more firms are likely to patent automation innovation upon treatment. However, we want to confirm if, on the intensive margin, the automation content of innovation



(a) Effect on automation patents



(b) Effect on non-automation patents

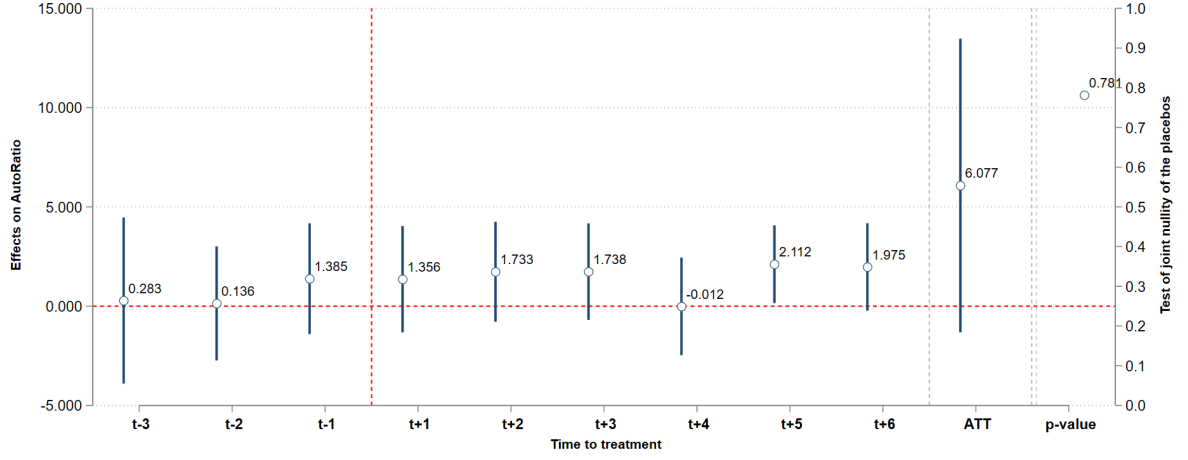
Figure 4: This Figure shows the dynamic effects of within-LLM increases to common ownership (*ContTreatLLM*) on the automation and non-automation patents.

increases due to more automation patents and not because of a decrease in non-automation patents.

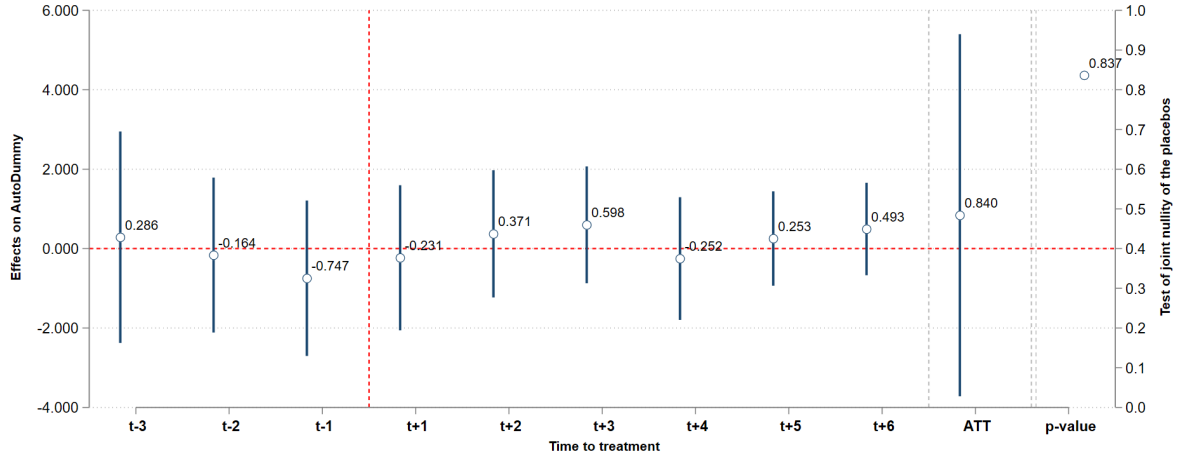
The results are shown in Figure 4. Treated firms experience a surge in automation patent output. The ATT is highly significant and indicates an increase of 43.8%. In years two to four, the significant increase in the number of automation patents is between 9.9% and 10.6%.

On the contrary, the ATT as well as the yearly effects on non-automation patents are not statistically different from zero.

The results shown in this section are robust to using the discrete treatment, as well as using patent citations to compute the automation strategy measures. Furthermore, we have also estimated the effects for our sample until 2006 and in pooled regressions including



(a) Using the continuous measure *AutoRatio*



(b) Using the binary measure *AutoDummy*

Figure 5: This Figure shows the dynamic effects of across-LLM increases to common ownership (*ContTreatnotLLM*) on the automation strategy of firms.

observations of firms treated by the placebo treatment without LLM rivalry. The results are qualitatively similar. The robustness checks can be found in Section C of the Appendix.

Overall, our results suggest that increases in common ownership between firms that compete for workers increase their automation-related innovation output. In the next section, we will use our alternative treatment to study the effect of common ownership on automation when labor market rivalry is absent.



### 3.5.2 Common Ownership and Automation Innovation in the Absence of Labor Market Rivalry

We now study how increases in common ownership affect firms' automation strategy in the absence of labor market rivalry using the treatment *ContTreatnotLLM*. That is, we focus on the change in automation innovation of those focal firms that experience an increase in common ownership with other firms outside the commuting zones in which the focal firms operate. Thus, we test Hypothesis 2.

The results are shown in Figure 5. The ATTs for both, the continuous *AutoRatio* and the binary *AutoDummy* are insignificant. Furthermore, most of the yearly effects are not statistically different from zero. Also, in terms of magnitude, the effects are much smaller than for those firms experiencing increases in common ownership with LLM rivals. The results corroborate Hypothesis 2.

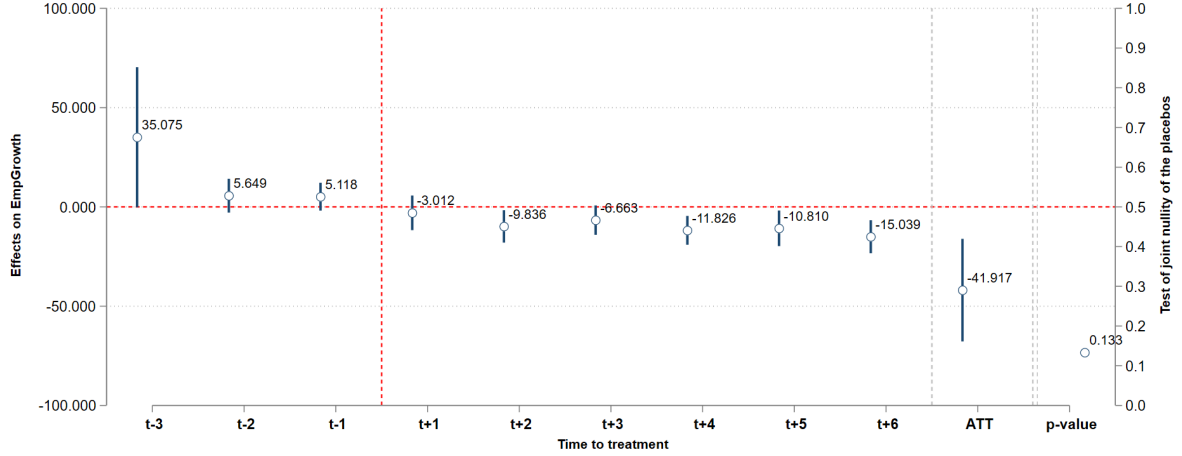
### 3.5.3 The Employment Effects of Common Ownership under Labor Market Rivalry

We have shown that increases in firms' common ownership within local labor markets affect firms' automation strategy. Increases in within-LLM common ownership raise the automation content of firms' innovation output. We now turn to the outcomes in terms of employment. Using our treatment *ContTreatLLM*, we now estimate the effect of common ownership within labor markets on firms' hiring decisions, applying *EmpGrowth* and *EmpIncrease* as the outcome variables. The results are shown in Figure 6.

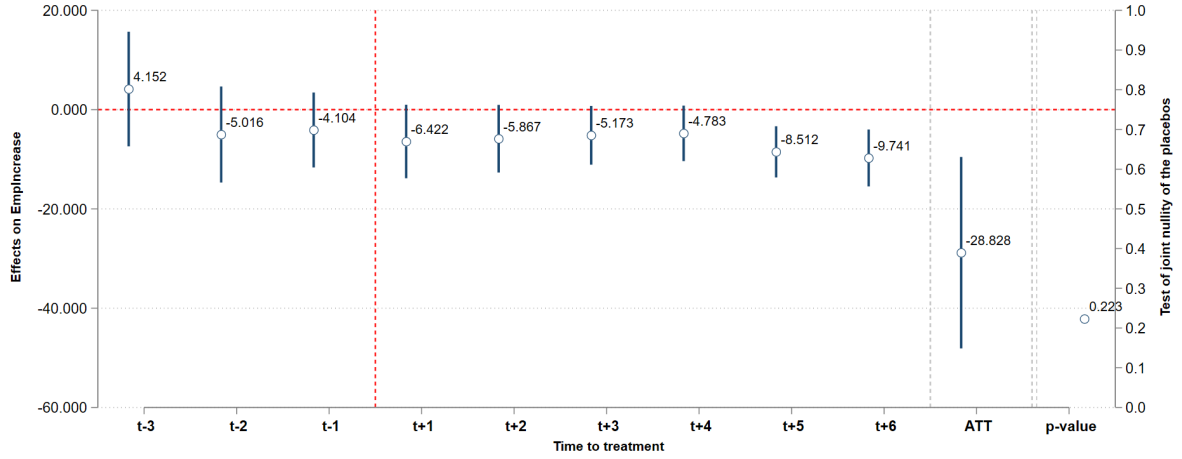
In the six years after the treatment event firms' growth rates in terms of employment and their likelihood of having positive employment growth both decrease significantly. On a yearly basis, their growth rates decrease by more than 9 percentage points in year two and more than 10 percentage points in the years four to six after the event. Their probability of experiencing positive growth rates in employment decreases by 4.7 to 9.7 percentage points (7.8% to 16.2% of the unconditional mean).

## 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



(a) Using the continuous measure *EmpGrowth*



(b) Using the binary measure *EmpIncrease*

Figure 6: This Figure shows the dynamic effects of within-LLM increases to common ownership (*ContTreatLLM*) on firms' growth in terms of employment.

the direction of technological change, steering portfolio firms to focus more on automation in their innovation process. Moreover, we do not find evidence that exogenous changes in common ownership of a focal firm with those companies that operate in distinct labor markets cause an increase in automation. This result is consistent with the mechanism we developed in our model. That is, institutional common ownership increases firms' incentives to automate to reduce labor market competition among portfolio firms. Consistent with this mechanism, 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.<sup>15</sup> 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.

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<sup>15</sup>See [Acemoglu and Restrepo \(2018\)](#), [Moll et al. \(2022\)](#), [Santini \(2024\)](#).

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# Appendix

## A Theory

*Proof.* To prove proposition 1, we proceed in two steps. First, we prove the proposition for a much simpler setting with two firms and one 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  $j$ , which has a degree of Common Ownership with firm  $-j$  with which also shares a local labor market,

$$\begin{aligned}
 & \max \quad p_j Y_j - r K_j - w(L) L_j + \lambda (p_{-j} Y_{-j} - r K_{-j} - w(L_j + L_{-j}) L_{-j}) \\
 & \text{subject to} \\
 & Y_j = \exp \left( \int_0^1 \ln [y_j(x)] dx \right)^\nu \\
 & y_j(x) = \gamma_m(x) m_j(x) + \gamma_\ell(x) l_j(x) \\
 & K_j = \int_0^I m_j(x) dx \\
 & L_j = \int_I^1 l_j(x) dx
 \end{aligned} \tag{11}$$

Given the assumption regarding the comparative advantage structure, the FOCs of the problem are,

$$\begin{aligned}
 [m(x)] & \implies m(x) = \frac{Y}{r} \nu \\
 [\ell(x)] & \implies \ell(x) = \frac{Y}{W} \nu \\
 [I] & \implies \frac{\gamma_\ell(I_j)}{\gamma_m(I_j)} = \frac{W}{r}
 \end{aligned} \tag{12}$$

with  $W$  being equal to the marginal cost of labor, e.g.,

$$W = w(L) + w'(L)(L_j + \lambda L_{-j}). \tag{13}$$

Rearranging the FOCs, we obtain that the solution to the problem of the firms is the solution to the two-equation two-unknowns problem. The system of equations is,<sup>16</sup>

$$\begin{aligned} L_j &= (1 - I_j) \left( \frac{W}{\nu} \right)^{\frac{I_j \nu - 1}{1 - \nu}} \left[ G \left( \frac{\nu}{r} \right)^{I_j} \right]^{\frac{\nu}{1 - \nu}} \\ W &= w(L) + w'(L)(L_j + \lambda L_{-j}). \end{aligned} \quad (14)$$

and the unknowns are  $L_j$  and  $W$ . Recall that both  $I_j$  and  $G$  are also functions of  $W$ . We need to prove that as Commonw Ownership,  $\lambda$ , 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  $I_j$ —see the FOC in 12. To proceed with the analytical proof, we need to specify the functional forms of the productivity schedules. These are,

$$\gamma_m(x) = e^{\alpha_m x} \quad (15)$$

$$\gamma_\ell(x) = e^{\alpha_\ell x} \quad (16)$$

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

$$I = \frac{1}{\alpha_\ell - \alpha_m} \log \left( \frac{W}{r} \right) \quad (17)$$

To characterize the solution of the system in 14, we first prove that the function represented by the first equation,  $L_j = g_d(W)$  is decreasing, that is, as the marginal cost of labor goes up, the labor demand decreases. To begin, take logs,

$$\log(L) = \log(1 - I) + \frac{I\nu}{1 - \nu} (\log(W) - \log(\nu) + \log\left(\frac{\nu}{r}\right)) - \frac{1}{1 - \nu} \log(W) + \frac{1}{1 - \nu} \log(\nu) + \frac{\nu}{1 - \nu} \log(G) \quad (18)$$

take the derivative with respect to  $W$

$$\frac{\partial}{\partial W} \log(L) = \frac{\partial I}{\partial W} \left[ \frac{\nu}{1 - \nu} \log\left(\frac{W}{r}\right) - \frac{1}{1 - I} \right] + \frac{I\nu - 1}{(1 - \nu)W} + \frac{\nu}{1 - \nu} \frac{1}{G} \frac{\partial G}{\partial W} \quad (19)$$

now substitute the derivative of  $G$

$$\frac{\partial G}{\partial W} = -G \log\left(\frac{W}{r}\right) \frac{\partial I}{\partial W} \quad (20)$$

---

<sup>16</sup>Recall that

$$G = \exp \left( \int_0^I \log[\gamma_m(x)] dx + \int_I^1 \log[\gamma_\ell(x)] dx \right)$$

and obtain,

$$\frac{\partial}{\partial W} \log(L) = \frac{\partial I}{\partial W} \left[ \frac{\nu}{1-\nu} \log\left(\frac{W}{r}\right) - \frac{1}{1-I} \right] + \frac{I\nu-1}{(1-\nu)W} - \frac{\nu}{1-\nu} \log\left(\frac{W}{r}\right) \frac{\partial I}{\partial W} \quad (21)$$

by rearranging we obtain,

$$\frac{\partial}{\partial W} \log(L) = -\frac{\partial I}{\partial W} \frac{1}{1-I} + \frac{I\nu-1}{(1-\nu)W} \quad (22)$$

Which is always negative because  $0 < I < 1$  and  $0 < \nu < 1$ . As the function  $L_j = g_d(W)$  is decreasing, the inverse  $W = g_d^{-1}(L_j)$  exists and is also decreasing. As the second equation of the system 14 is increasing, we can plot the two functions and derive the properties of the solution. In Figure 7 we plot two scenarios. One in which the level of Common Ownership is  $\lambda^1$  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 (17), an increase in  $W_j$  implies an increase in  $I_j$ .

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  $\lambda_{fj}$  increases the level of automation in the local labor market  $I_f^c$  which consequently, increases the automation *average* across local labor markets,

$$I_f \equiv \frac{1}{|\mathbf{C}_f|} \sum_{\mathbf{C}_f} I_f^c. \quad (23)$$

□

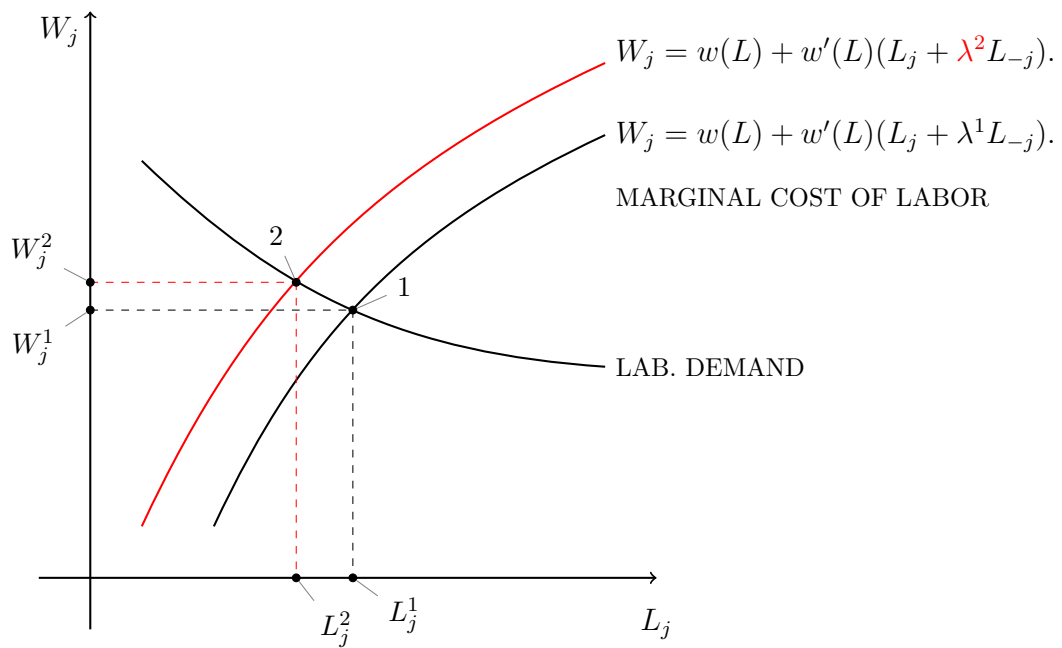


Figure 7: This figure plots the labor demand curve and the curve of the marginal factor cost of labor for two different values of common ownership,  $\lambda_2 > \lambda_1$ . It shows that as common ownership goes up employment decreases and the marginal cost of labor increases.

## B OLS Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	$AutoRatio_{t+1}$	$AutoRatio_{t+2}$	$AutoRatio_{t+3}$	$AutoRatio_{t+4}$	$AutoRatio_{t+5}$	$AutoRatio_{t+6}$
<i>CindexLLM</i>	10.984* (6.548)	14.011** (7.128)	15.129** (7.531)	20.794** (8.423)	18.119** (8.706)	4.121 (10.090)
<i>InstOwn</i>	0.006 (0.075)	-0.022 (0.077)	0.037 (0.077)	0.053 (0.077)	0.088 (0.081)	-0.001 (0.086)
<i>R&amp;DtoAssets</i>	0.130*** (0.046)	0.117** (0.052)	0.054 (0.047)	0.030 (0.037)	0.043 (0.041)	0.078 (0.056)
<i>FirmSize</i>	0.115*** (0.024)	0.095*** (0.022)	0.072*** (0.021)	0.047** (0.020)	0.034 (0.021)	0.029 (0.022)
<i>FirmAge</i>	-0.158*** (0.044)	-0.174*** (0.045)	-0.223*** (0.045)	-0.233*** (0.045)	-0.231*** (0.047)	-0.233*** (0.047)
<i>EmptoAssets</i>	1.571 (3.124)	1.544 (3.098)	2.704 (3.067)	2.968 (3.119)	3.672 (3.032)	2.424 (2.939)
<i>PPEtoAssets</i>	-0.181 (0.111)	-0.102 (0.115)	-0.057 (0.121)	-0.054 (0.127)	-0.120 (0.136)	-0.102 (0.138)
Firm-FE	YES	YES	YES	YES	YES	YES
Industry-Year-FE	YES	YES	YES	YES	YES	YES
Observations	16032	14805	13534	12291	11082	9935
<i>Adj.-R</i> <sup>2</sup>	0.708	0.718	0.728	0.742	0.747	0.760

Table 4: This Table presents OLS estimates of firms’ automation strategy on common ownership with LLM rivals. Standard errors in parenthesis are clustered at the firm level. Significance levels are indicated as follows: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## C Robustness

### C.1 Using citation-weighted Patents

In studies concerning innovation, it is standard to control for the quality of patents by using citation counts. We also have estimated our models concerning innovation outcomes on the intensive margin using citation-weighted patents, applying the “time-technology class fixed effect” method (Hall et al., 2001; Atanassov, 2013), to address truncation problems.

With these adjusted patent citations, we compute our continuous innovation outcome variables. That is,

$$AutoRatioCites = \ln \left[ \frac{1 + \text{citation-weighted automation Patents}}{1 + \text{citation-weighted non-automation Patents}} \right],$$

as well as  $\ln AutoCites$  and  $\ln NonAutoCites$ , which are the natural logarithm of (one plus) the citation-weighted number of Patents for automation and non-automation, respectively.

The results are shown in Figure 8.

## C.2 Using a pooled sample for both treatments

In this section, we test if our main results on within-LLM changes of common ownership on firms’ automation strategy are robust to the data cleaning procedure. In our baseline results in the main text of the paper, we have eliminated firms from the sample that are affected by a merger, but not jointly with LLM rivals when estimating the effect of common ownership of LLM rivals. Here, we keep these observations in the sample. The results of this exercise are shown in Figure 9. The results are qualitatively similar to our baseline: An increase in common ownership with LLM rivals leads to increases in the automation innovation output, both on the intensive and extensive margins.

## C.3 Using data before the onset of the financial crisis

In this section, we address the concern that our results may be driven by abnormalities during the financial crisis. We present the same analysis as in the main text of our paper, but using only data up to 2006. That means, we also exclude the last seven mergers in the sample of institutional mergers identified by [Lewellen and Lowry \(2021\)](#), including the merger between BlackRock and Barclays Global Investors, which was used for identification in previous studies.<sup>17</sup> The results are shown in Figure 10.

## C.4 Using the binary treatment setup

In this Section, we present the results of the DID analysis employing the binary treatment variable *TreatLLM* as defined in Section 3.2.4. The results are shown in Figure 11.

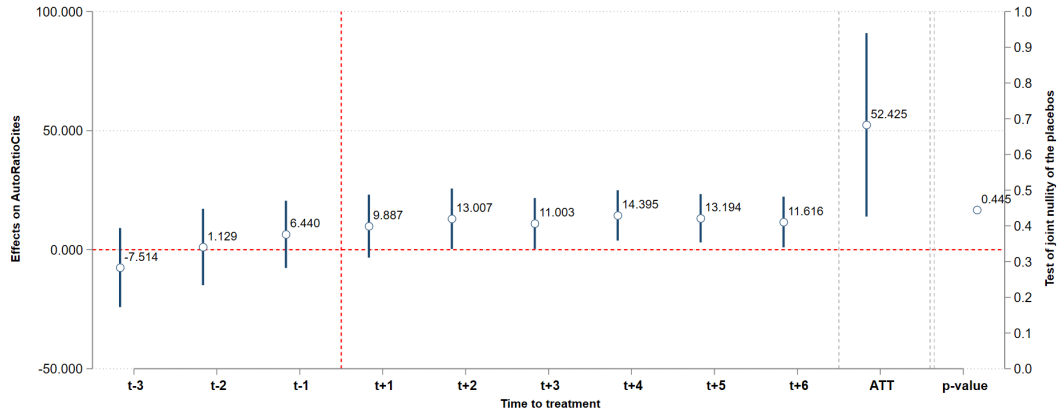
# A Database Construction

**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.

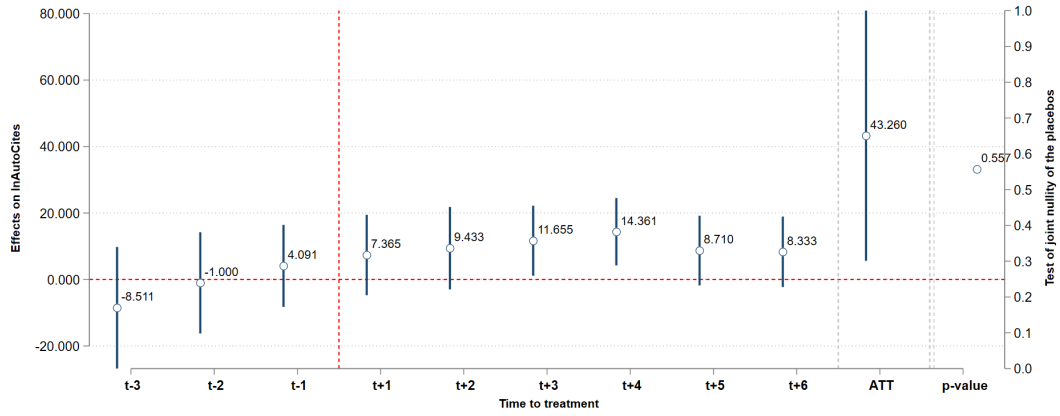
We utilize fuzzy matching, employing a similarity threshold of 90%, to align company names between the two databases. Subsequently, we conduct manual verification to ensure the precision of these matches. With this methodology, we successfully merge 353,818 establishments. It results in a dataset of 4,231,721 establishment-year observations for the

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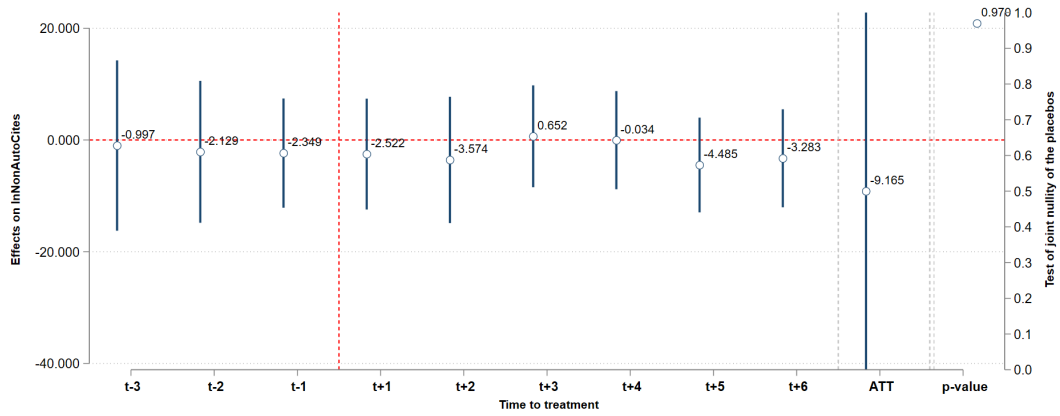
<sup>17</sup>See, e.g., [Azar et al. \(2018\)](#).



(a) Using *AutoRatioCites* as dependent variable.



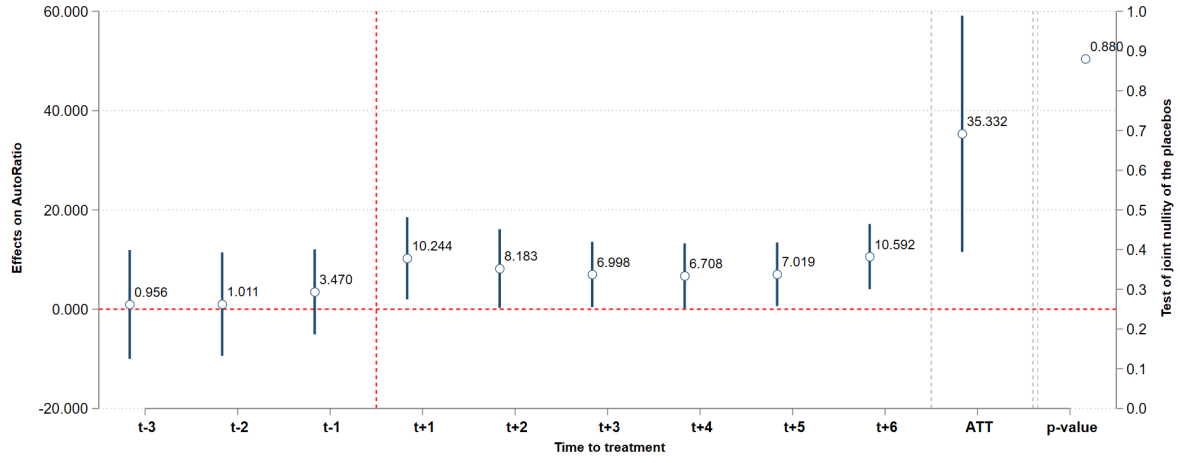
(b) Using *lnAutoCites* as dependent variable.



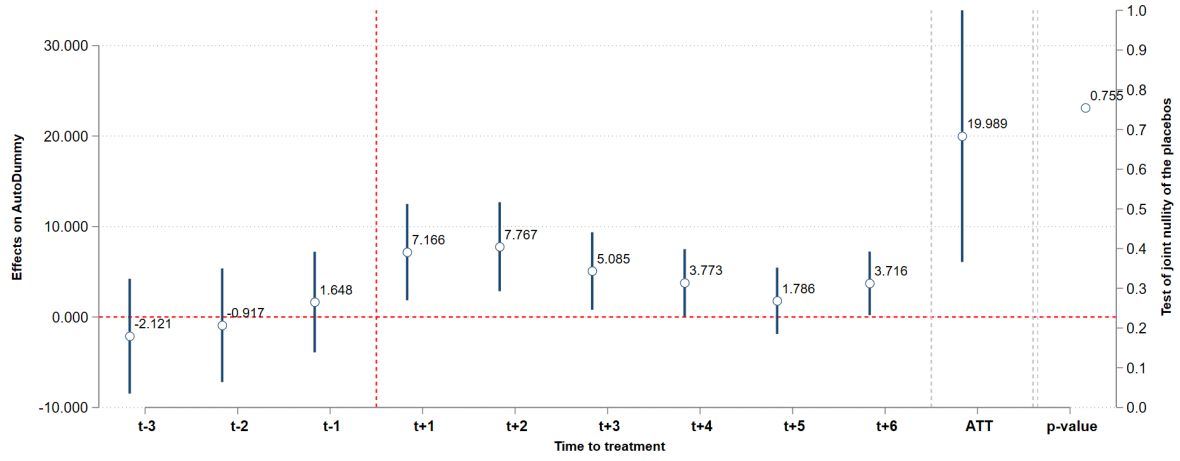
(c) Using *lnNonAutoCites* as dependent variable.

Figure 8: This Figure shows the dynamic effects of within-LLM increases to common ownership (*ContTreatLLM*) on the automation strategy of firms based on citation-weighted patent counts.





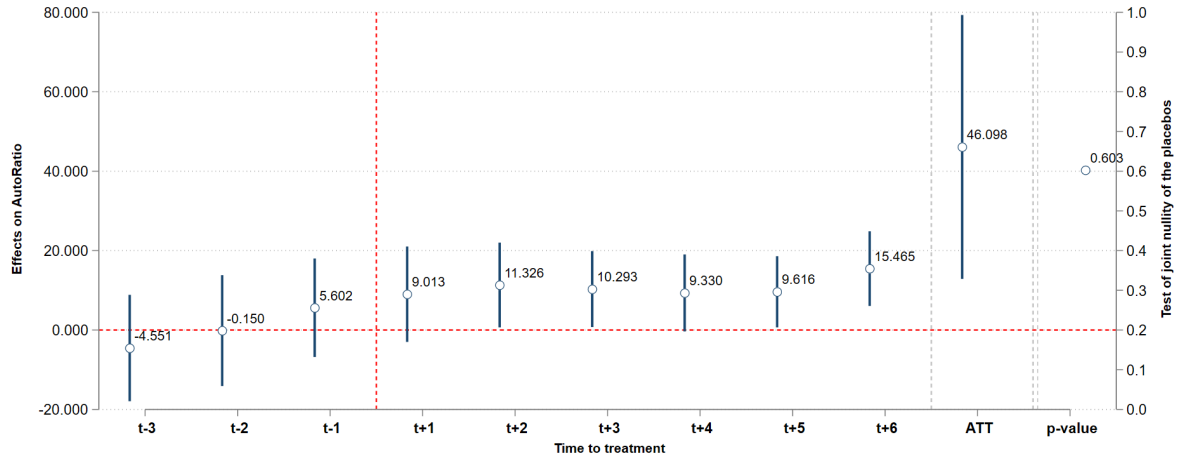
(a) Using the continuous measure *AutoRatio*



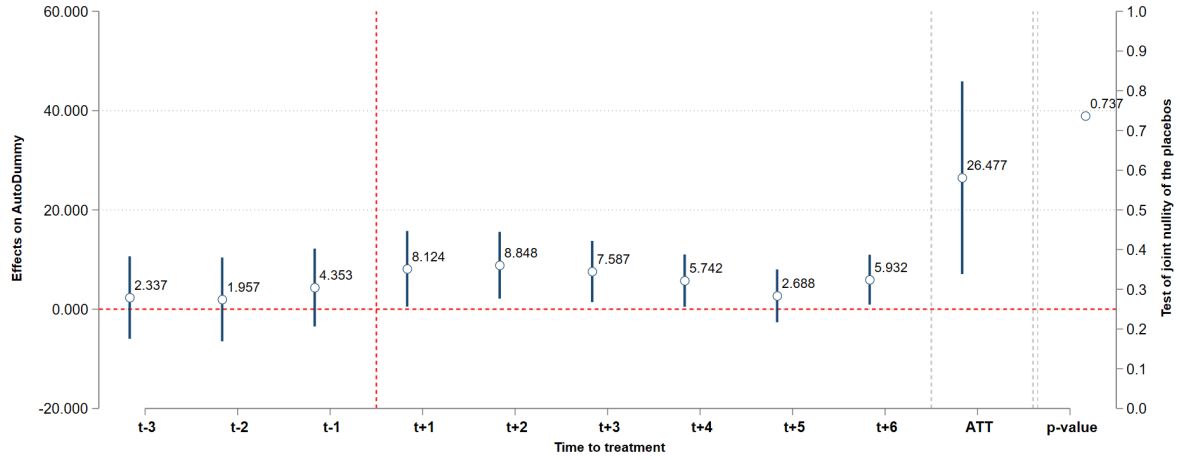
(b) Using the binary measure *AutoDummy*

Figure 9: This Figure shows the dynamic effects of within-LLM increases to common ownership (*ContTreatLLM*) on the automation strategy of firms in a pooled sample. This sample contains observations of those firms treated by *ContTreatnotLLM* in some years.

spanning period 1990-2020, each containing no missing information on employee count and geographical location.

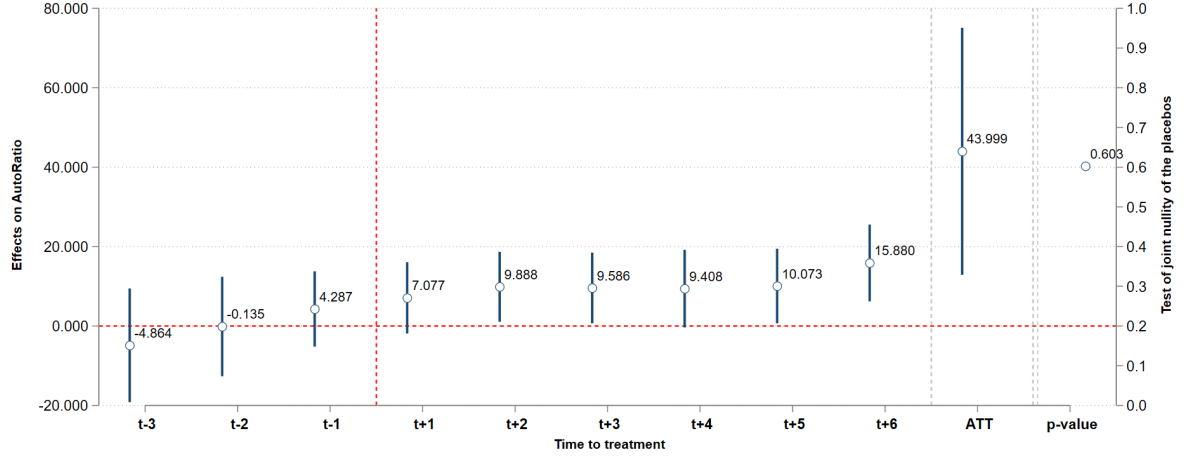


(a) Using the continuous measure *AutoRatio*

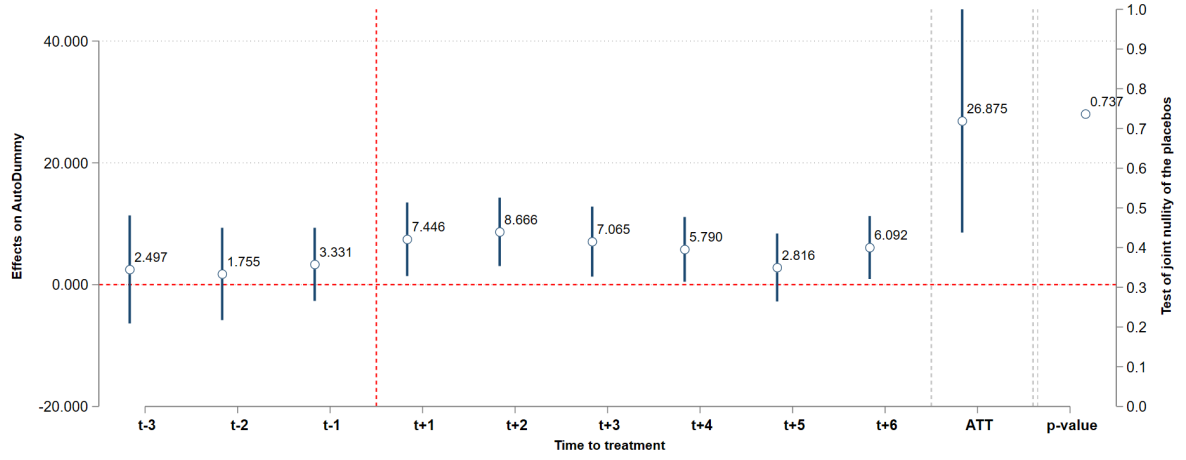


(b) Using the binary measure *AutoDummy*

Figure 10: This Figure shows the dynamic effects of within-LLM increases to common ownership (*ContTreatLLM*) on the automation strategy of firms using data until 2006, i.e., before the onset of the financial crisis.



(a) Using the continuous measure *AutoRatio*



(b) Using the binary measure *AutoDummy*

Figure 11: This Figure shows the dynamic effects of within-LLM increases to common ownership using a binary treatment variable ( $Treat_{LLM}$ ) on the automation strategy of firms.



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