Labor Cost Induced Innovation

DuckKi Cho*, Buhui Qiu†

This Version: March 2026

ABSTRACT

We estimate the causal effect of labor costs on corporate innovation using cross-state and time-series variation in statutory minimum wages as plausibly exogenous labor-cost shocks. Using firm-level patent and citation data, we find that higher labor costs lead to economically meaningful increases in innovation quantity and quality. The results are robust to complementary identification strategies based on federally mandated wage increases and a stacked difference-in-differences design centered on large, discrete shocks. The effects are strongest among financially flexible firms and firms with greater exposure to minimum-wage labor. Wage increases also shift innovation toward AI- and automation-related technologies, raise R&D investment, and improve innovation efficiency. Finally, firms with stronger innovation capacity reallocate toward more capital-intensive production and experience gains in performance and labor productivity, highlighting innovation as a key channel of adaptation to rising labor costs.

Keywords: Labor Costs, AI-Innovation, Technological Change, Capital-Labor Substitution

JEL Codes: J31, O31, O33, G30

*University of Sydney Business School, The University of Sydney; Email: d.cho@sydney.edu.au.
†University of Sydney Business School, The University of Sydney; Email: buhui.qiu@sydney.edu.au.

I. Introduction

Labor costs are a fundamental component of firms' production decisions and a central focus of public policy debates. From a theoretical perspective, increases in the price of labor may compress margins and dampen investment in innovation. The same wage pressure may also induce firms to reorganize production, substitute capital for labor, and pursue productivity-enhancing innovation, as emphasized in models of induced innovation and directed technical change (Zeira, 1998; Acemoglu and Restrepo, 2018). Whether higher wages ultimately hinder or stimulate technological progress has far-reaching implications for firm competitiveness, how firms adapt to changing labor market conditions, and the broader consequences of wage regulation. Yet despite the prominence of this question in theory and policy discussions, systematic firm-level evidence on how labor costs reshape corporate innovation, production choices, and performance remains limited.

In this study, we estimate the causal effect of labor costs on corporate innovation. Identifying this effect is challenging because wage-setting is jointly determined with firms' investment, hiring, and innovation decisions. To address this concern, we exploit substantial cross-state and time-series variation in statutory minimum wage rates as a source of plausibly exogenous shocks to firms' labor costs. This identification strategy relies on the assumption that changes in state minimum wage laws are plausibly exogenous to firm-level innovation outcomes.

Our focus on minimum wage variation is motivated by a large literature on skill-biased technological change, which shows that computerization and industrial robotics reduce the relative demand for low-skill labor (Autor, Katz, and Krueger, 1998; Autor, Levy, and Murnane, 2003; Graetz and Michaels, 2018). In these frameworks, rising low-skill wages strengthen incentives to adopt labor-saving technologies (Hémous and Olsen, 2022). Accordingly, wage shocks that disproportionately affect low-skilled labor provide

a useful setting to study firms' innovation responses along automation and productivity-enhancing margins. Moreover, Akerlof and Yellen (1990) and Engbom and Moser (2022) suggest that minimum wage increases can generate compensation pressures beyond directly affected workers, as firms adjust internal pay structures to preserve morale and pay differentials, further supporting our empirical strategy.

Under this framework, we link firm-level innovation outcomes to changes in effective minimum wage exposure while controlling for firm fixed effects, industry-by-year shocks, and local macroeconomic conditions. We estimate the reduced-form effect of higher labor costs on innovation using fixed effects Poisson models to appropriately account for the count nature of patent and citation data. The baseline results show that increases in minimum wages are associated with economically and statistically meaningful gains in patenting activity and forward citations. In the most stringent specification, a one-standard-deviation increase in the minimum wage leads to a 7.9% (12.3%) increase in the number of patents (forward citations). These patterns suggest that rising wage pressures incentivize firms to intensify innovation efforts, leading them to adopt labor-saving technologies or improve production processes to offset higher labor costs.

A potential concern is that unobserved state-level shocks correlated with local investment opportunities could influence both state minimum wage statutes and corporate innovation, violating the identifying assumption. To strengthen identification, we corroborate our baseline findings using two complementary approaches.

First, we exploit federally mandated minimum wage adjustments, which are largely determined at the national level and are therefore plausibly orthogonal to state-specific economic conditions that could influence firm-level innovation. Specifically, we classify a state as bound if its statutory minimum wage is absent or set at or below the federal level, such that a federal minimum wage increase directly raises the applicable wage floor (Clemens and Wither, 2019). Using a difference-in-differences framework, we compare firms in bound states to those in unbound states around three federal reforms during the

sample period. The estimates show that firms headquartered in bound states experience a statistically significant increase in innovation following federal wage hikes, relative to firms in unbound states where state minimum wages already exceed the federal rate. In particular, exposure to a binding federal increase is associated with a 7.4% rise in patenting and an 8.3% increase in forward citations following the wage shock. These findings closely mirror the results based on state-level variation and further support a causal interpretation.

Second, to address recent concerns about potential bias in two-way fixed effects difference-in-differences models with staggered treatment timing (e.g., de Chaisemartin and D'Haultfoeuille, 2020; Borusyak, Jaravel, and Spiess, 2024; Callaway, Goodman-Bacon, and Sant'Anna, 2024), we adopt a stacked difference-in-differences design that focuses on discrete, large minimum wage shocks. In particular, we define events as substantial state-level wage increases that exceed three times the contemporaneous inflation rate and construct a stacked dataset that aligns treated and control firms in event time while restricting controls to firms that remain untreated over the relevant window. The results remain consistent with our baseline findings: firms exposed to large labor cost shocks experience a statistically significant increase in innovation activity, with treated firms exhibiting an 8.3% (7.6%) rise in patenting (citations) relative to comparable control firms.

In addition, we examine dynamic responses of innovation to labor cost shocks by estimating event-time specifications that trace year-to-year changes for treated firms relative to control firms. The estimates show no evidence of differential pre-trends, supporting the parallel trends assumption underlying our identification strategy. Following the wage shocks, innovation outcomes rise persistently for treated firms, consistent with a causal post-treatment increase in patenting activity and quality.

To bolster the causal interpretation of our findings, we examine cross-sectional heterogeneity along two key dimensions: financial flexibility and exposure to minimum-

wage labor. The results show that the positive relation between minimum wage increases and innovation is stronger among firms with greater financial slack, suggesting that the availability of financial resources plays an important role in enabling firms to invest in innovation when facing higher wage bills. In addition, the effect is more pronounced in industries that employ a larger share of workers earning near the statutory minimum, consistent with stronger payroll pressures in these sectors driving improvements in innovation. These patterns reinforce the causal interpretation and indicate that rising labor costs stimulate innovation, particularly when firms face direct wage pressure and have the financial capacity to expand investment in productivity-enhancing innovation.

To probe the mechanisms underlying positive innovation responses, we examine the types of technologies developed as well as innovation inputs and efficiency. Consistent with a labor-saving channel, higher labor costs are associated with a stronger tilt toward AI- and automation-related technologies among firms operating in minimum-wage-sensitive industries. These firms also increase R&D investment and improve innovation efficiency, suggesting that rising wage pressures not only stimulate innovation investment but also encourage a more efficient allocation of innovation resources.

We next examine how a firm's ex-ante innovation capacity shapes its input mix adjustments to rising labor costs. Using R&D stock as a proxy for accumulated innovation capacity, we find that firms with stronger innovative capabilities respond to wage shocks by systematically altering their input mix. In particular, high-innovation-capacity firms reduce employment and simultaneously increase their capital-labor ratios following increases in minimum wages, consistent with a shift toward more capital-intensive and technology-driven production. These findings provide direct evidence that innovation facilitates labor-saving adjustments, enabling firms to substitute capital and advanced technologies for labor as wage pressures intensify.

We further show that these adjustments translate into meaningful performance outcomes. While increases in labor costs are associated with declines in firm value for firms

with little or no innovation capacity, firms with stronger innovative capabilities exhibit a positive valuation response. Consistent with this pattern, more innovative firms also experience improvements in operating profitability and labor productivity following wage shocks. Collectively, these results indicate that innovation capacity plays a central role in helping firms adapt to higher labor costs by reconfiguring production toward more efficient, capital-intensive processes, ultimately supporting resilience in firm value and operating performance.

This study adds to the growing literature on labor and finance, as surveyed in Pagano and Volpin (2008) and Nishesh, Ouimet, and Simintzi (2024), by studying how labor costs shape firm-level innovation, input reallocation, and performance. Our findings reveal that differences in firms' financial flexibility and innovation capacity play a pivotal role in determining how effectively they adapt to changes in labor market conditions. In particular, wage increases can spur technological adoption and productivity-enhancing innovation, consistent with the theoretical framework of Zeira (1998). These results suggest that the effects of wage increases may extend beyond direct cost pressures to broader general equilibrium implications.

Only a limited number of studies have examined how labor market conditions influence firm-level innovation. Acharya, Baghai, and Subramanian (2014) and Bena, Ortiz-Molina, and Simintzi (2022), for example, document that stronger employment protection can promote innovation through distinct mechanisms. The former emphasizes stronger inventor incentives arising from mitigating employer hold-up problems, while the latter highlights firm incentives to invest in process innovation to adapt to labor rigidity. In contrast, we study statutory wage shocks that directly raise firms' labor costs through higher mandated pay, rather than institutional reforms that indirectly influence labor costs via changes in employment protection. We further contribute by examining AI-related innovation as a margin of adjustment, capturing cost-saving technological adoption that enables firms to substitute capital for labor and implement more

efficient production processes. This setting allows us to revisit the broader question of how increases in labor prices shape corporate innovation and production decisions.

Hémous, Olsen, Zanella, and Dechezleprêtre (2025) is the closest to our setting. However, our study differs along several important dimensions. First, while their analysis focuses on how labor costs faced by downstream firms affect upstream innovation, we examine how increases in a firm's own labor costs shape its innovation, input reallocation, and performance. Second, they primarily study patents in the machinery sector, whereas we examine overall innovation across firms and analyze AI- and automation-related innovation not only as a means of substituting for labor but also as a broader channel for reducing production costs. Third, our analysis provides a comprehensive account of how firms respond to labor cost shocks by documenting not only their innovation responses but also the roles of financial flexibility, changes in R&D investment and innovation efficiency, input reallocation toward capital-intensive production, and the resulting implications for firm value, profitability, and labor productivity. Finally, their identification relies on reduced-form variation in country-level minimum wages, whereas we triangulate the causal effect using three complementary identification strategies within a single country, thereby strengthening internal validity.

The rest of the paper is organized as follows. Section II describes the data, sample construction, and measures of corporate innovation. Section III examines the impact of labor cost shocks on corporate innovation, outlining the institutional background, identification strategies, and robustness checks. Section IV investigates cross-sectional heterogeneity with respect to financial flexibility and exposure to minimum-wage workers. Section V explores the labor-saving mechanisms by focusing on AI-related innovation and the channels through which labor cost shocks translate into enhanced innovation outcomes. Section VI studies how firms' innovation capacity shapes their responses to rising labor costs through input mix adjustments and performance. VII provides concluding remarks.

II. Main Variables and Sample

A. *Measuring Corporate Innovation*

We obtain the extended patent dataset originally used in Kogan, Papanikolaou, Seru, and Stoffman (2017).[1] This database contains detailed patent and citation information spanning 1926-2023, with patent records linked to CRSP PERMNO identifiers. It provides comprehensive information on patent issuing and filing dates, forward citations, and technological classification based on the full CPC (Cooperative Patent Classification) class, among other attributes.

To gauge firm-level innovation activities, we construct two standard measures capturing the quantity and quality of innovation output, following prior studies (e.g., He and Tian, 2013; Balsmeier, Fleming, and Manso, 2017; Guo, Pérez-Castrillo, and Toldrà-Simats, 2019). The first measure is the number of patent applications filed by a firm in a given year that are eventually granted. We assign patents to years based on their application dates rather than grant dates, as application timing more closely reflects the period in which the underlying innovation occurs (Hall, Jaffe, and Trajtenberg, 2001). Because patent counts alone do not distinguish between incremental and more influential innovations, we construct the second measure of innovation by aggregating the number of forward citations received by a firm's patents filed in a given year and ultimately granted.

Forward citations accumulate gradually over time, which creates a truncation problem in measuring innovation quality. Older patents have a longer window to receive citations than more recent ones, mechanically inflating their citation counts relative to patents filed closer to the end of the sample period. For example, patents applied for in

[1] We downloaded the version released on October 7, 2024, from `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`. We thank Noah Stoffman and his coauthors for making these data publicly available.

1995 have had substantially more time to accumulate citations than those applied for in 2020, even if their underlying technological impact is comparable. To address this concern, we follow Hall et al. (2001) and subsequent studies such as He and Tian (2013) and Guo et al. (2019) and implement a time–technology class adjustment. Specifically, we normalize the number of forward citations received by each patent by the average number of citations for patents granted in the same year and within the same CPC technology class.[2] This procedure accounts for differences in citation opportunities across cohorts and technological domains, thereby mitigating bias arising from differential exposure to citation accumulation.

B. Sample Construction and Descriptive Statistics

We consider a sample of firms listed in the Compustat database during the period 1985-2021. Although the patent database extends through 2023, we exclude the final two years (2022–2023) to mitigate truncation concerns. Because the lag between a patent's application and grant dates is substantial—about 2 years on average (He and Tian, 2013)—many applications filed in recent years have not yet been granted by 2023. As a result, using these observations would mechanically understate the number of successful patent applications and introduce downward bias in measured innovation. Restricting the sample to 1985–2021 ensures that most applications have sufficient time to be processed and granted, improving the reliability of our innovation measure.

Following a sample-selection approach similar to that of Bloom, Schankerman, and Van Reenen (2013), we include all non-financial (excluding SIC codes 6000-6999) and non-utility (excluding SIC codes 4900-4999) firms headquartered in the U.S. that filed at least one patent application (eventually granted) with the United States Patent and Trademark Office (USPTO) during the sample period, yielding a total of 51,129 firm-year observations.

[2]We use the first listed CPC class in the full classification string as a patent's primary technology class.

To identify each firm's exposure to state-level minimum wage policies and local economic conditions, we link firms to the historical state of their headquarters using data provided by Bai, Fairhurst, and Serfling (2020) and the University of Notre Dame's Software Repository for Accounting and Finance (Loughran and McDonald, 2016). This historical mapping allows us to construct a consistent firm–state panel for merging with state-level policy and economic variables. For firms without available historical location data, we instead rely on the state of headquarters reported in the header file, which reflects the most recent location.

Insert Table I here.

The summary statistics of all main variables are reported in Table I, with detailed definitions and variable construction provided in Appendix Table A1. All dollar-denominated variables are converted to December 2021 constant dollars using the Consumer Price Index for All Urban Consumers, and all continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers.

For the average firm in our sample, the number of patent applications per year is 16.6 over the entire sample period, with substantial dispersion reflected in a standard deviation of 52.1. The distribution is highly right-skewed, as indicated by a median of 1, suggesting that most firm-year observations involve relatively modest patenting activity, while a relatively small group of firms accounts for a large share of total innovation output. The number of adjusted forward citations per year exhibits a similar pattern, with a mean of 15.8, a standard deviation of 48.7, and a median of 1. This concentration is consistent with prior evidence that both the quantity and impact of innovation are unevenly distributed, with a limited set of firms generating a disproportionate share of high-value inventions.

The key explanatory variable, *Min Wage*, captures the effective hourly minimum wage faced by each firm, measured as the weighted average of the applicable hourly minimum wage in its headquarters state, with weights reflecting the number of days

each rate is in effect within a given year. The mean value of *Min Wage* is \$6.0, with a standard deviation of \$2.1. These figures indicate meaningful cross-sectional and intertemporal variation in wage floors across states and over time, providing the empirical variation necessary to identify the effect of changes in labor costs on firms' innovation activity.

III. The Impact of Labor Cost Shocks on Corporate Innovation

Identifying the causal effect of labor costs on corporate innovation is inherently challenging because wage-setting is typically determined jointly with other corporate policies, including R&D investment and innovation strategies. To address this endogeneity concern and establish causal inference, we exploit cross-state and time-series variation in statutory minimum wage rates as a source of plausibly exogenous shocks to firms' labor costs.

A. Institutional Details

The federal minimum wage provisions in the United States are established under the Fair Labor Standards Act (FLSA), which governs employees in the private sector as well as in federal, state, and local governments. The Act applies to employers with annual sales of at least \$500,000 or those engaged in interstate commerce and sets standards for minimum wages, overtime pay, recordkeeping, and youth employment. Enacted in 1938 and amended repeatedly (primarily to raise the federal minimum wage), the FLSA covered more than 143 million workers across over 9.8 million workplaces as of July 2009, the date of the most recent federal minimum wage adjustment. The Act is administered and enforced by the U.S. Department of Labor's Wage and Hour Division.

In addition to federal regulation, many states implement their own minimum wage

policies. These state-level standards may be indexed to inflation, adjusted through scheduled legislative increases, set equal to the federal rate, or determined by a combination of these approaches. As a result, minimum wage levels vary across states and over time. Under Section 18 of the FLSA, when workers are subject to both federal and state regulations, they are entitled to the higher of the two wage floors. This institutional structure generates meaningful cross-state heterogeneity in binding wage requirements, which we exploit for identification.

Importantly, minimum-wage-induced labor cost shocks are not limited to workers earning at or near the statutory minimum. Prior theoretical and empirical work (Akerlof and Yellen, 1990; Engbom and Moser, 2022) shows that worker effort depends on the ratio of actual wages to perceived fair wages. When minimum wages increase, firms may face pressure—albeit to varying degrees—to maintain internal wage hierarchies and avoid reductions in morale among higher-paid workers. Consequently, changes in minimum wage rates can propagate beyond directly affected employees, creating broader adjustments in compensation structures and firm-wide labor costs.

B. Identification Strategy

Our identification strategy relies on the assumption that changes in federal and state minimum wage laws are plausibly exogenous to firm-level innovation outcomes. As a baseline, we estimate the reduced-form effect of state minimum wage rates on corporate innovation using the following specification:

$$y_{i,t} = \alpha_i + \alpha_{j,t} + \beta_1 \, Min\ Wage_{i,t-1} + \beta_2 \, X_{i,t-1} + \beta_3 \, Z_{s,t-1} + \epsilon_{i,t}, \tag{1}$$

where i, s, j, and t index firm, headquarters state, two-digit SIC industry, and year, respectively. The dependent variable, $y_{i,t}$, is one of the innovation measures, either *Num Patents* or *Num Citations*. The key explanatory variable, $Min\ Wage_{i,t-1}$, captures

the effective hourly minimum wage faced by firm i, measured as the weighted average of the applicable hourly minimum wage in its headquarters state, with weights based on the number of days each rate is in effect during year $t-1$.

The vector X includes standard lagged firm-level controls following Atanassov (2013) and He, Leung, Qiu, and Zhou (2025): market-to-book assets, $\ln(M/B)$; firm size, $\ln(Assets)$; book leverage, *Leverage*; operating profitability, $Profitability$; asset tangibility, *Tangibility*; and R&D expenditures, $R\&D$. We also include lagged state-level controls, $Z_{s,t-1}$, comprising real GDP growth rates, *State GDP Growth*; log population, $\ln(State\ Population)$; and unemployment rates, *State Unemp Rate*. Appendix Table A1 provides detailed variable definitions. Lastly, α_i denotes firm fixed effects that control for time-invariant firm heterogeneity, while $\alpha_{j,t}$ represents industry-by-year fixed effects that absorb time-varying shocks common to firms within the same industry. In all specifications, standard errors are clustered at the state level, as minimum wage policies vary by state and may induce correlation in unobserved factors affecting firms headquartered in the same location.[3]

We estimate Equation (1) using fixed effects Poisson regressions. Prior work cautions that OLS models using the log of one plus patent or citation counts as the dependent variable can produce biased estimates. In contrast, fixed-effects Poisson specifications, which model count outcomes directly, yield consistent and relatively efficient estimates under more general conditions (Cohn, Liu, and Wardlaw, 2022; Chen and Roth, 2024).[4]

As discussed in Section III.A, states adjust their minimum wages through different mechanisms. Some index minimum wages to inflation to preserve real purchasing power, others legislate future increases that may reflect anticipated local economic conditions, and some adopt the federal minimum wage. When inflation or improving (local)

[3]Clustering standard errors at the firm level yields qualitatively similar results.

[4]Our baseline findings remain significant when estimating Equation (1) using OLS specifications in which the dependent variable is the logarithm of one plus the number of patents or citations.

investment opportunities trigger wage increases, the identifying assumption may be violated to the extent that those same factors also influence innovation.

To mitigate this concern, we include state-by-year fixed effects in our conditional analyses (Sections IV.B to V.B) to absorb unobservable state-level, time-varying economic conditions that are potentially tied to state minimum wage policies. This approach helps ensure that identification is not driven by coincident state-specific trends in investment opportunities or economic activity. In addition, changes in the federal minimum wage are largely determined at the national level and are plausibly orthogonal to state-specific economic conditions affecting individual firms. This feature provides a cleaner source of variation that is less likely to be confounded by local macroeconomic shocks. We exploit this advantage further in Section III.1 by using federal minimum wage adjustments to conduct additional robustness tests of the baseline results.

C. Baseline Results Using State-level Minimum Wage Laws

Insert Table II here.

Table II reports the results from fixed effects Poisson regressions of corporate innovation on the minimum wage variable, introduced in Section III.B. In columns (1)-(4), the dependent variable is the number of patent applications filed in a given year that are eventually granted (*Num Patents*). Column (1) includes firm and year fixed effects without additional time-varying controls. Column (2) replaces year fixed effects with industry-by-year fixed effects to account for industry-level changes in investment opportunities. Columns (3) and (4) mirror the specifications in columns (1) and (2), respectively, while additionally incorporating time-varying firm- and state-level control variables.

The estimates indicate that minimum-wage-induced increases in labor costs lead to a statistically significant rise in innovation output across all specifications. The economic magnitude is also meaningful. In the most stringent specification (column 4), the

estimated coefficient on *Min Wage* is 0.036. A one–standard-deviation increase in the minimum wage ($2.112) is therefore associated with a 0.076 log-point increase in patenting activity ($= 0.036 \times 2.112$), which corresponds to approximately a 7.9% increase in the number of patents ($= e^{0.076} - 1$).

In columns (5)-(8), we shift the focus from patent quantity to quality by using the number of adjusted forward citations to patents filed in a given year as the dependent variable. The results mirror the earlier findings: the estimated coefficients on *Min Wage* remain positive and statistically significant across all specifications. In the most stringent specification column (8), the point estimate of 0.055 implies that a one-standard-deviation increase in the minimum wage is associated with a 0.116 log-point rise in citation counts ($= 0.055 \times 2.112$). This translates into an economically meaningful effect of roughly a 12.3% ($= e^{0.116} - 1$) increase, indicating that higher labor costs not only promote greater patenting activity, as firms innovate to accommodate increased wage pressure presumably through automation, but also enhance the impact and quality of innovative output.

D. Alternative Identification Strategies

1. Using Federal Minimum Wage Laws

Our baseline estimates exploit variation in state-level minimum wage changes, treating them as plausibly exogenous to firm-level innovation. While reasonable, such changes may coincide with local economic conditions, including inflation or investment opportunities, that could independently influence innovation activity. To sharpen identification, we restrict attention to federally mandated minimum wage adjustments that bind at the state level, following the approach in Clemens and Wither (2019).

During our sample period (1985-2021), federal minimum wage legislation was enacted on (i) November 17, 1989, (ii) August 20, 1996, and (iii) May 25, 2007. These leg-

islative changes translated into stepwise increases in the federal minimum wage: from \$3.35 to \$3.80 in April 1, 1990, and to \$4.25 in April 1, 1991; to \$4.75 in October 1, 1996, and to \$5.15 in September 1, 1997; and following the 2007 reform, to \$5.85 in July 24, 2007, to \$6.55 in July 24, 2008, and to \$7.25 in July 24, 2009.

We classify a state as bound if it either lacks a state-level minimum wage or maintains a statutory minimum wage at or below the federal level over the window spanning one year before to three years after the first effective date of each cluster of federal increase.[5] This definition ensures that the federal policy is a binding constraint throughout the period in which we assess its impact on innovation. All other states are treated as unbound. We then implement a difference-in-differences design, restricting the sample to the three-year window around each event.

$$\begin{aligned} y_{i,t} =& \alpha_i + \alpha_{j,t} + \beta_1 \, Bound_{s,t} \times Post_{i,t}^{fed} + \beta_2 \, Bound_{s,t} + \beta_3 \, Post_{i,t}^{fed} \\ &+ \beta_4 \, X_{i,t-1} + \beta_5 \, Z_{s,t-1} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where $Bound_{s,t}$ is an indicator equal to one if, at time t, a firm is headquartered in state s for which the federal minimum wage is binding, and $Post_{i,t}^{fed}$ is an indicator that takes the value one for event years 1 through 3.[6] The coefficient of interest is β_1, which is expected to be positive. A positive estimate would indicate that firms exposed to a federally mandated increase in labor costs generate more patents and receive more forward citations relative to firms in unbound states that are not directly affected by the federal minimum wage hike.

Insert Table III here.

[5]Specifically, we define event year 1 as the first fiscal year ending after the initial effective date of the wage increase. For instance, for the November 1989 reform, event year 1 corresponds to fiscal years ending between April 1, 1990, and March 31, 1991. Other event years are defined relative to this benchmark.

[6]Note that $Bound_{s,t}$ is not absorbed by firm fixed effects because some states are bound in one event but not in another. Likewise, $Post_{i,t}^{fed}$ is not subsumed by year (or industry-by-year) fixed effects, as firms have different fiscal year-ends and the federal minimum wage changes were implemented in different months.

The estimation results are reported in Table III. Columns (1) and (2) use *Num Patents* as the dependent variable, while columns (3) and (4) use *Num Citations*. Columns (1) and (3) include firm and year fixed effects along with time-varying controls, whereas Columns (2) and (4) replace year fixed effects with industry-by-year fixed effects. The estimated coefficient on the interaction term is positive and statistically significant in all four specifications. In column (2), the estimate of 0.071 implies that firms exposed to a federally mandated increase in labor costs generate approximately 7.4% ($=e^{0.071}-1$) more patents following the wage shock, relative to firms in unbound states.

The results for forward citations are also similar and consistent with the baseline estimates based on the state-level minimum wage variation in Table II. Specifically, the estimated coefficient of 0.080 in column (4) corresponds to an 8.3% increase in patent forward citations. Taken together, the results in Table III provide consistent support for the view that higher labor costs prompt firms to intensify innovation activity, likely as a means of offsetting the adverse impact of rising wages on their operations. In Section V.A, we further examine types of innovations induced by higher labor costs to shed light on underlying mechanisms.

2. Using Stacked Difference-in-Differences

Recent econometric work (e.g., de Chaisemartin and D'Haultfoeuille, 2020; Borusyak et al., 2024; Callaway et al., 2024) highlights that two-way fixed effects (TWFE) difference-in-differences models with staggered treatment timing can yield biased estimates when treatment effects are heterogeneous over time or across groups. Callaway et al. (2024) study a TWFE framework with continuous treatment intensity, similar to Equation (1), and decompose the estimand into a causal response component and a selection bias component. The causal response captures the average causal change in innovation outcomes associated with a one-unit increase in the minimum wage, whereas selection bias arises from differences in average treatment effects across groups facing different wage

levels.

They show that eliminating selection bias requires a strong parallel trends assumption: the average innovation path for the entire population, if all firms had been exposed to a given wage level w, must coincide with the observed innovation trajectory of the group actually facing that wage level w. In their framework, treatment is absorbing in that once a unit is treated, it remains exposed to the same treatment intensity. In contrast, in our context, firms facing a minimum wage level w may later be subject to a higher statutory rate $w'(> w)$. This evolving treatment intensity complicates the mapping between TWFE estimands and underlying building-block parameters, limiting the direct applicability of their results to our setting.

To address potential biases arising from heterogeneous treatment effects, we adopt the stacked regression approach following Cengiz, Dube, Lindner, and Zipperer (2019), with minor modifications. We define an event as a large minimum-wage shock, measured as an increase in the statutory minimum wage exceeding three times the contemporaneous inflation rate, based on the consumer price index for all urban consumers. We then binarize the continuous minimum wage variable (*Min Wage*) using the indicator (*Treated*), which is set to one for such large shocks. To ensure a clean identification of discrete events, we require that no other minimum wage shocks occur within the window [−5, 1] around the event.

We then construct a stacked dataset by aligning all event-specific observations in event time over a seven-year window [−3, +3], rather than calendar time. To avoid "forbidden" comparisons, we impose a stringent criterion for control firms: candidate control firms must not experience any treatment during the window [−5, +3], that is, they must be either never-treated or not-yet-treated over the relevant horizon. This design helps isolate the effect of large minimum wage shocks while minimizing contamination from overlapping treatment episodes.

Using the stacked dataset, we estimate the following difference-in-differences speci-

fication:

$$y_{i,c,t} = \alpha_{i,c} + \alpha_{j,c,t} + \beta_1 \, Treated_{i,c} \times Post_{c,t} + \beta_2 \, X_{i,c,t-1} + \beta_3 \, Z_{s,c,t-1} + \epsilon_{i,c,t}, \tag{3}$$

where c indexes cohort, $Treated_{i,c}$ is an indicator for firms exposed to a large minimum wage shock, and $Post_{c,t}$ is an indicator for years following the event. The main effects of $Treated_{i,c}$ and $Post_{c,t}$ are absorbed by the cohort-specific fixed effects. The coefficient of interest is β_1, which captures the differential change in innovation for treated firms after the shock relative to control firms. A positive estimate would indicate that firms facing large labor cost increases subsequently generate more patents and receive more forward citations than their untreated counterparts.

The estimation results are documented in Table IV. The estimated coefficients on the interaction terms are positive and statistically significant at the 1% level across all four specifications. The estimate of 0.080 (0.073) in column (2) (column (4)), for instance, implies that treated firms experience an 8.3% (7.6%) increase in patenting activity (forward citations) following large labor cost shocks relative to control firms, consistent with the baseline estimates in Table II.

These findings provide important reassurance regarding identification. By focusing on discrete, large shocks and employing the stacked design, the specification mitigates concerns that TWFE estimates may be driven by negative weighting or contamination from heterogeneous treatment effects. The persistence of positive and economically meaningful coefficients in this setting suggests that our baseline results are not an artifact of staggered treatment timing or differential treatment dynamics. Instead, they reinforce the interpretation that increases in labor costs causally stimulate firms' innovation activity, supporting the robustness of the main conclusions.

3. Dynamic Analyses

In this section, we examine the dynamic response of firm-level innovation to labor cost shocks by estimating year-to-year changes in outcomes for treated firms relative to control firms around the event, building on the empirical settings in Sections III.1 and III.2. This approach provides a more granular view of the timing and persistence of the treatment effects.

Beyond tracing the adjustment path of innovation, the dynamic specification enables us to assess the parallel trend assumption underlying our difference-in-differences framework. A causal interpretation requires that treated and control firms exhibit similar pre-treatment trends in innovation. By examining whether innovation trajectories evolve similarly prior to the wage shock and diverge only afterward, the dynamic analyses provide supporting evidence for this identifying assumption.

Insert Figure I here.

To this end, we replace the *Post* indicator in Equations (2) and (3) with a set of event-time indicators (d_t) and reestimate the models. Figure I, based on the modified Equation (2), plots the estimated coefficients on the interaction between *Bound* and d_t, along with 95% confidence intervals, where the x-axis denotes years relative to the federal minimum wage shock. The estimates show no discernible difference in pre-treatment trends of innovation outcomes between firms in bound (treated) and unbound (control) states. Following the shock, both patent quantity and quality rise for treated firms, consistent with a post-treatment increase in innovation activity.

Insert Figure II here.

Similarly, Figure II, based on the modified Equation (3), plots the estimated coefficients on the interaction between *Treated* and d_t. The results closely mirror those in Figure I, reinforcing the absence of pre-trends and the positive post-shock response in innovation among firms facing higher labor costs.

IV. Labor Cost Induced Innovation: Cross-sectional Heterogeneity

After establishing a causal link between labor costs and corporate innovation, we explore heterogeneity along two dimensions to shed light on underlying mechanisms and further bolster the causal interpretation of our findings. First, we examine variation by financial flexibility. Firms with greater financial slack are better positioned to respond to increases in wage expenses by expanding innovative activity, whereas financially constrained firms may lack the capacity to undertake such investments when labor input becomes more costly. Second, we analyze differential effects across firms with varying exposure to minimum-wage workers. This test helps verify that the observed increase in innovation outputs is indeed driven by heightened payroll pressures associated with a higher share of low-wage labor.

A. Financial Flexibility

To capture financial flexibility, we employ five proxies commonly used in the literature: the HP Index (Hadlock and Pierce, 2010), the KZ index (Kaplan and Zingales, 1997; Lamont, Polk, and Saá-Requejo, 2001), the WW index (Whited and Wu, 2006; Hennessy and Whited, 2007), an indicator for dividend-paying status (Farre-Mensa and Ljungqvist, 2016), and the excess price cost margin (Gaspar and Massa, 2006). Detailed definitions and variable construction are provided in Appendix Table A1.

Using these proxies (excluding the dividend-payer indicator), we construct indicator variables that identify firms in the top and bottom terciles of each proxy's cross-sectional distribution in a given year. Since adverse wage shocks may directly affect a firm's financial flexibility, we construct these indicator variables using information from two years prior to the innovation outcomes (i.e., one year before the wage shocks). We then interact

Min Wage in Equation (1) with each of these indicator variables, one at a time, to estimate heterogeneous treatment effects across levels of financial flexibility. We additionally include interaction terms between the control variables and each financial flexibility indicator, as these controls may have differential effects on innovation outcomes depending on a firm's level of financial flexibility.

Insert Table V here.

Panel A of Table V presents the estimation results based on the HP Index. The estimated coefficients on the interaction terms between *Min Wage* and FF_{HP} are positive and statistically significant at the 5% level or higher across all four specifications. These findings indicate that the innovation response to higher labor costs is more pronounced among financially flexible firms, which are better positioned to expand innovation investment. The magnitude of the estimated coefficients also exceeds that from the unconditional analyses in Table II. For example, financially flexible firms (those in the bottom tercile of the HP index) generate about 6.5% ($= e^{0.063} - 1$) more patent applications for a one-dollar increase in the hourly minimum wage, whereas the corresponding increase for the average firm is approximately 3.7% ($= e^{0.036} - 1$).

Panels B-E of Table V corroborate the findings in Panel A using four alternative proxies for financial flexibility. Across these specifications, 14 of the 16 interaction coefficients are positive and statistically significant, providing consistent evidence that financial flexibility amplifies firms' innovation response to higher labor costs. Overall, these results indicate that access to financial slack is an important enabling factor in sustaining innovation investment when firms face adverse wage shocks.

B. Minimum Wage Sensitive Industries

If improvements in corporate innovation outcomes are driven by increased labor cost pressures, the relation between minimum wages and innovation should be more pronounced among firms employing a larger share of workers earning wages near the

statutory minimum. To capture this heterogeneity, we use worker characteristics data from the Bureau of Labor Statistics' Current Population Survey (2017) to identify industries differentially exposed to minimum wage changes. Specifically, industries are classified as highly (less) exposed if the share of hourly workers earning at or below the prevailing federal minimum wage is above (below) the sample median.

We construct an indicator variable, *MW Ind*, equal to one if a firm's primary industry falls into the high-exposure group. We then interact *Min Wage* with *MW Ind* in Equation (1) to estimate cross-sectional differences in the innovation response to labor cost shocks. As in the previous section, we include interaction terms between the control variables and *MW Ind*, as these controls may have differential effects on innovation outcomes depending on a firm's employment composition. We also replace industry-by-year fixed effects with state-by-year fixed effects because *MW Ind* is defined at the industry level. This specification also provides a robustness check, as our baseline model cannot accommodate state-by-year fixed effects that would otherwise absorb unobservable, time-varying local economic conditions.

Insert Table VI here.

Table VI reports the results. Consistent with our conjecture, the estimated coefficients on the interaction terms are positive and statistically significant across all four specifications. These findings indicate that the innovation-enhancing effect of minimum-wage increases is more pronounced among firms operating in industries that rely more on minimum-wage workers. Importantly, in columns (2) and (4), the coefficients remain economically large and statistically significant even after including state-by-year fixed effects, alleviating concerns that the results are driven by unobservable local investment opportunities that may simultaneously raise wages and innovation activities.

V. Innovation Types, Input, and Efficiency

A. AI-Related Innovation

In this section, we present additional analyses to interpret our main findings through the lens of a labor-saving mechanism. As firms face rising labor costs, they have stronger incentives to develop technologies that substitute for labor and improve production efficiency. To capture this channel, we focus on AI-related patent applications as a proxy for cost-saving innovation, drawing on the Artificial Intelligence Patent Dataset (AIPD) 2023 developed by Pairolero, Giczy, Torres, Islam Erana, Finlayson, and Toole (2025).

Their methodology uses a supervised machine-learning text classification model trained on patent documents to assign each patent a predicted probability of being AI-related based on its technical language and content. The classification draws on eight AI component technologies: knowledge processing, speech, AI hardware, evolutionary computation, natural language processing, machine learning, computer vision, and planning/control.

We adopt their classification and define AI-related patents using probability thresholds of 50%, 86%, and 93%, which progressively capture broader to more conservative sets of AI innovations. Using this classification, we construct *Ratio of AI Patent* as the fraction of a firm's AI-related patent applications filed in a given year that are ultimately granted. We then estimate fixed-effects OLS regressions of this ratio on the interaction between the minimum wage (*Min Wage*) and an indicator for minimum-wage-sensitive industries (*MW Ind*). This specification allows us to assess whether increases in labor costs are associated with a greater tilt toward successful AI-related innovation among firms more exposed to minimum wage pressures.

Insert Table VII here.

Panel A of Table VII presents the estimation results across three probability thresh-

olds used to classify AI relevance. Consistent with the labor-saving mechanism, the estimated coefficients on the interaction terms are positive and statistically significant at the 5% level or better in all six columns. These findings suggest that firms operating in minimum-wage-sensitive industries have stronger incentives to develop AI-related technologies that may help mitigate the adverse effects of rising labor costs. The results are robust to alternative probability thresholds for defining AI-related patents.

Among the eight AI component technologies identified by Pairolero et al. (2025), AI hardware, machine learning, computer vision, and planning/control are more directly related to automation that may substitute for costly labor. To assess the robustness of the results in Panel A of Table VII, we focus on these automation-oriented AI technologies and construct *Ratio of AUTO-AI Patent* as the fraction of a firm's automation-related AI patent applications filed in a given year that are ultimately granted. The results reported in Panel B of Table VII closely mirror those in Panel A, providing further support for the labor-saving mechanism.

B. Innovation Input and Efficiency

To further shed light on the mechanisms through which labor cost shocks translate into enhanced innovation outcomes—both in terms of quantity and quality—we examine their effects on firms' innovation inputs and efficiency. If higher labor costs stimulate innovation by inducing firms to substitute toward technology, one would expect not only an increase in innovation output but also greater investment in R&D and potentially more efficient conversion of R&D inputs into patentable outcomes.

We adopt a specification similar to that in the previous section (except that we exclude R&D from the set of control variables), where the dependent variable is either R&D expenses ($R\&D$) or innovation efficiency ($Innov\ Eff$). $R\&D$ is measured as annual R&D expenditures scaled by total assets. $Innov\ Eff$ is defined as the ratio of *Num Patents* to $R\&D$ *Stock*, where $R\&D$ *Stock* is constructed using the perpetual-inventory method

with a 15% knowledge depreciation rate. Detailed variable definitions and construction procedures are provided in Appendix Table A1.

Insert Table VIII here.

The results are documented in Table VIII. The dependent variable is $R\&D$ in columns (1) and (2). The estimated coefficients on the interaction terms are positive and statistically significant at the 1% level, indicating that labor cost shocks prompt firms, particularly those operating in minimum-wage-sensitive industries, to increase their R&D investment. This pattern is consistent with the enhanced innovation outcomes documented in Table VI.

Sustaining improvements in both the quantity and quality of innovation in the face of rising labor costs likely requires firms to allocate R&D resources more efficiently. To reconcile the earlier findings, we therefore examine innovation efficiency by using $Innov\ Eff$ as the dependent variable in columns (3) and (4). The estimated coefficients on the interaction terms are positive and statistically significant at the 1% level, indicating that firms exposed to higher labor cost pressures not only increase R&D investment but also convert these inputs into patent output more efficiently. This evidence further reinforces the interpretation that labor cost shocks induce a more productive use of innovation resources.

VI. Role of Innovation Ability in Input Mix Adjustments and Performance

In this section, we examine how labor-cost–induced innovation reshapes firms' input choices and performance. We focus on the role of ex-ante innovation ability in shaping firms' responses to rising labor costs. Firms with stronger innovative capacity are better positioned to adjust production processes, adopt new technologies, and substitute away from labor as wage pressures intensify (Jones, 2005). Studying heterogeneity along this

dimension, therefore, helps clarify whether the adjustment in input mix and enhanced performance reflect the deployment of innovation capabilities in response to labor cost shocks.

A. The Effect of Labor Cost Shocks on Employment and Capital Intensity

We proxy for innovation ability using a firm's stock of knowledge, measured by its R&D stock (Bloom et al., 2013), which captures the accumulated inputs into the innovation process. *R&D Stock* is calculated using the perpetual inventory method with a 15% knowledge depreciation rate. To assess how innovation ability shapes input adjustments following labor cost increases, we estimate regressions of ln(*Employees*) and ln(*Capital-Labor Ratio*) on the interaction between *Min Wage* and ln(1+*R&D Stock*), where *Employees* denotes the number of employees, and *Capital-Labor Ratio* is the ratio of property, plant, and equipment to the number of employees.

Because adverse wage shocks may themselves influence a firm's innovation capacity, we measure innovation ability using information from two years prior to the innovation outcomes (i.e., one year before the wage shocks). This timing mitigates concerns that contemporaneous changes in R&D investment mechanically confound the interpretation of firms' ex-ante innovative capacity. In addition to the control variables included in the baseline specification, we further control for capital expenditures, cash and cash equivalents, annual sales growth, past stock returns, and past stock return volatility. Detailed variable definitions are provided in Appendix Table A1.

Insert Table IX here.

In Table IX, columns (1) and (2) use the level of employment as the dependent variable. The estimated coefficients on the interaction terms are negative and statistically significant at the 1% level in both specifications. These findings are consistent with the notion that firms with greater innovation capacity reduce their reliance on labor in response to rising wage pressures, likely facilitated by improved innovation outcomes that

enable the adoption of more labor-saving technologies.

In economic terms, the estimates imply a meaningful contraction in employment among high-innovation-capacity firms when labor costs increase. For instance, in column (2), a firm with an R&D stock one standard deviation above the sample mean (7.321 in logs) reduces its employment by approximately 2.5% in response to a one-dollar increase in the hourly minimum wage ($\approx 0.022 - 0.006 \times 7.321$), which is significant at the 1% level (t-statistics = –5.52).[7]

A complementary pattern emerges for the capital–labor ratio. When we use the capital–labor ratio as the dependent variable in columns (3) and (4), the estimated coefficients on the interaction terms are positive and remain statistically significant at the 1% level in both columns. In column (4), a firm with an R&D stock one standard deviation above the sample mean increases its capital-labor ratio by roughly 2.5% in response to a one-dollar increase in the hourly minimum wage ($\approx -0.044 + 0.010 \times 7.322$), which is significant at the 1% level (t-statistics = 3.16).[8]

These patterns indicate a systematic shift in the input mix: firms with stronger innovation capacity substitute capital for labor following wage shocks. Taken together, the results provide direct support for the labor-saving mechanism, whereby enhanced innovation—particularly AI- and automation-related technologies—facilitates the reallocation of production toward more capital-intensive processes in response to higher labor costs.

[7]The reported 2.5% decrease is calculated using the full-precision coefficient estimates from the regression output. Recalculating the effect using rounded coefficients (0.022 and 0.006) yields approximately 2.2%, with the difference attributable to rounding.

[8]The reported 2.5% increase is calculated using the full-precision coefficient estimates from the regression output. Recalculating the effect using rounded coefficients (–0.044 and 0.010) yields approximately 2.9%, with the difference attributable to rounding.

B. *The Effect of Labor Cost Shocks on Firm Value, Profitability, and Labor Productivity*

We next examine whether labor-cost–induced innovation, and the associated shift toward more capital-intensive production, translates into improved firm performance. If innovation enables firms to substitute away from costly labor and adopt more efficient and innovative production processes, such adjustments should help mitigate the adverse effects of rising wage pressures on operating outcomes. To evaluate this implication, we employ an empirical strategy similar to that in the previous section and analyze how firms' ex-ante innovation capacity shapes the response of firm value, profitability, and labor productivity to labor cost shocks. In doing so, we assess whether innovation not only alters input choices but also supports broader performance resilience in the face of higher labor costs.

Insert Table X here.

In columns (1) and (2) of Table X, the dependent variable is *Tobin's q* as a proxy for firm value. The estimated coefficient on *Min Wage* is negative and statistically significant, suggesting that hypothetical firms with no innovation capacity (i.e., those not engaging in R&D activities) experience a decrease in firm value following increases in labor costs, consistent with the evidence in Bell and Machin (2018). Importantly, the estimated coefficients on the interaction terms are positive and statistically significant in both specifications, indicating that innovation capacity helps mitigate this adverse effect on firm value.

To better understand the sources of the performance gains and equity value creation, we next examine operating profitability and labor productivity in columns (3)-(6). Consistent with the patterns in columns (1) and (2), the estimated coefficients on the interaction terms are positive and statistically significant at the 5% level or better across all four columns. For example, in column (4), a firm with an R&D stock one standard

deviation above the sample mean (7.318 in logs) increases its profitability by approximately 45 basis points in response to a one-dollar increase in the hourly minimum wage ($\approx -0.042 + 0.067 \times 7.318$), which is significant at the 5% level (t-statistics = 2.08). The corresponding increase in column (6) is about 3.3% ($\approx 0.003 + 0.004 \times 7.324$) in labor productivity, which is statistically significant at the 1% level (t-statistics = 3.80).

Overall, the results indicate that innovation capacity plays a key role in cushioning firms against the adverse effects of rising labor costs. Firms with stronger ex-ante innovative capabilities not only adjust their input mix toward more capital-intensive production but also experience improvements in profitability and labor productivity, which in turn support firm value. These findings suggest that labor-cost-induced innovation is not merely a defensive response but can translate into meaningful performance gains, highlighting the importance of innovation in sustaining competitiveness under wage pressure.

VII. Conclusion

This paper examines the causal impact of labor cost shocks on corporate innovation and the broader adjustments in firms' production choices and performance. Exploiting variation in state-level minimum wage changes, we document a robust positive relationship between rising labor costs and firm-level innovation. The baseline results show that increases in minimum wages lead to economically meaningful improvements in both the quantity and quality of innovation. A series of additional analyses based on federally mandated wage adjustments, stacked difference-in-differences designs, and dynamic event-time specifications, consistently support a causal interpretation. Cross-sectional analyses further reveal that these effects are stronger among financially flexible firms and among firms operating in industries with greater exposure to minimum-wage workers, reinforcing the view that heightened payroll pressure is a key driver of the observed innovation response.

We then explore the mechanisms underlying this innovation response. Firms exposed to higher labor costs increase R&D investment and improve the efficiency with which innovation inputs are converted into patent output. The shift toward AI- and automation-related innovation provides direct evidence consistent with a labor-saving channel. At the operational level, firms with stronger ex-ante innovation capacity reduce employment and increase capital intensity following wage shocks, indicating a reallocation of production toward more capital-intensive processes. Importantly, these adjustments are associated with improvements in firm value, profitability, and labor productivity, suggesting that labor-cost–induced innovation can serve as an effective margin of adaptation rather than merely a defensive response to labor cost pressures.

Taken together, the findings of the study show that wage increases can stimulate technologically oriented responses that reshape firms' input mix and enhance performance. From a policy perspective, the results suggest that higher minimum wages may have broader general equilibrium effects than typically considered, potentially accelerating technological adoption and productivity-enhancing investments. Importantly, however, the innovation response is substantially stronger among financially flexible firms, implying that these positive general equilibrium effects may be unevenly distributed across the corporate sector.

This heterogeneity raises a complementary policy concern: when wage floors rise, financially constrained firms may be less able to undertake the R&D investments and technology upgrades needed to adapt, potentially widening performance and productivity gaps. Policies that ease financing frictions, such as improving access to credit for innovative but constrained firms or strengthening innovation-support programs, may therefore amplify the aggregate efficiency gains from rising labor costs while mitigating disparities in firms' capacity to adjust.

References

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review 108, 1488–1542.

Acharya, V. V., Baghai, R. P., Subramanian, K. V., 2014. Wrongful discharge laws and innovation. Review of Financial Studies 27, 301–346.

Akerlof, G. A., Yellen, J. L., 1990. The fair wage-effort hypothesis and unemployment. Quarterly Journal of Economics 105, 255–283.

Atanassov, J., 2013. Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. Journal of Finance 68, 1097–1131.

Autor, D. H., Katz, L. F., Krueger, A. B., 1998. Computing inequality: Have computers changed the labor market? Quarterly Journal of Economics 113, 1169–1213.

Autor, D. H., Levy, F., Murnane, R. J., 2003. The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics 118, 1279–1333.

Bai, J. J., Fairhurst, D., Serfling, M., 2020. Employment Protection, Investment, and Firm Growth. Review of Financial Studies 33, 644–688.

Balsmeier, B., Fleming, L., Manso, G., 2017. Independent boards and innovation. Journal of Financial Economics 123, 536–557.

Bell, B., Machin, S., 2018. Minimum wages and firm value. Journal of Labor Economics 36, 159–195.

Bena, J., Ortiz-Molina, H., Simintzi, E., 2022. Shielding firm value: Employment protection and process innovation. Journal of Financial Economics 146, 637–664.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81, 1347–1393.

Borusyak, K., Jaravel, X., Spiess, J., 2024. Revisiting Event-Study Designs: Robust and Efficient Estimation. Review of Economic Studies p. rdae007.

Callaway, B., Goodman-Bacon, A., Sant'Anna, P. H. C., 2024. Difference-in-differences with a continuous treatment. NBER Working Paper .

Cengiz, D., Dube, A., Lindner, A., Zipperer, B., 2019. The Effect of Minimum Wages on Low-Wage Jobs. Quarterly Journal of Economics .

Chen, J., Roth, J., 2024. Logs with zeros? Some problems and solutions. Quarterly Journal of Economics 139, 891–936.

Clemens, J., Wither, M., 2019. The minimum wage and the great recession: Evidence of effects on the employment and income trajectories of low-skilled workers. Journal of Public Economics 170, 53–67.

Cohn, J. B., Liu, Z., Wardlaw, M. I., 2022. Count (and count-like) data in finance. Journal of Financial Economics 146, 529–551.

de Chaisemartin, C., D'Haultfoeuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review 110, 2964–2996.

Engbom, N., Moser, C., 2022. Earnings inequality and the minimum wage: Evidence from brazil. American Economic Review 112, 3803–3847.

Farre-Mensa, J., Ljungqvist, A., 2016. Do measures of financial constraints measure financial constraints? Review of Financial Studies 29, 271–308.

Gaspar, J., Massa, M., 2006. Idiosyncratic volatility and product market competition. Journal of Business 79, 3125–3152.

Graetz, G., Michaels, G., 2018. Robots at work. Review of Economics and Statistics 100, 753–768.

Guo, B., Pérez-Castrillo, D., Toldrà-Simats, A., 2019. Firms' innovation strategy under the shadow of analyst coverage. Journal of Financial Economics 131, 456–483.

Hadlock, C. J., Pierce, J. R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Review of Financial Studies 23, 1909–1940.

Hall, B. H., Jaffe, A. B., Trajtenberg, M., 2001. The NBER patent citation data file: Lessons, insights and methodological tools. NBER Working Paper Series pp. 8498–.

He, J. J., Tian, X., 2013. The dark side of analyst coverage: The case of innovation. Journal of Financial Economics 109, 856–878.

He, Q., Leung, H., Qiu, B., Zhou, Z., 2025. The effect of social media on corporate innovation: Evidence from seeking alpha coverage. Management Science 71, 5441–5476.

Hennessy, C. A., Whited, T. M., 2007. How costly is external financing? Evidence from a structural estimation. Journal of Finance 62, 1705–1745.

Hémous, D., Olsen, M., 2022. The rise of the machines: Automation, horizontal innovation, and income inequality. American Economic Journal: Macroeconomics 14, 179–223.

Hémous, D., Olsen, M., Zanella, C., Dechezleprêtre, A., 2025. Induced automation innovation: Evidence from firm-level patent data. Journal of Political Economy 133, 1975–2028.

Jones, C. I., 2005. The shape of production functions and the direction of technical change. Quarterly Journal of Economics 120, 517–549.

Kaplan, S. N., Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? Quarterly Journal of Economics 112, 169–215.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation and growth. Quarterly Journal of Economics 132, 665–712.

Lamont, O., Polk, C., Saá-Requejo, J., 2001. Financial constraints and stock returns. Review of Financial Studies 14, 529–554.

Loughran, T., McDonald, B., 2016. Textual analysis in accounting and finance: A survey. Journal of Accounting Research 54, 1187–1230.

Nishesh, N., Ouimet, P., Simintzi, E., 2024. Labor and corporate finance. In: Denis, D. J. (ed.), *Handbook of Corporate Finance*, Edward Elgar Publishing, Cheltenham, UK, Research Handbooks in Money and Finance series, pp. 647–673.

Pagano, M., Volpin, P., 2008. Labor and finance. London Buiness School, mimeo .

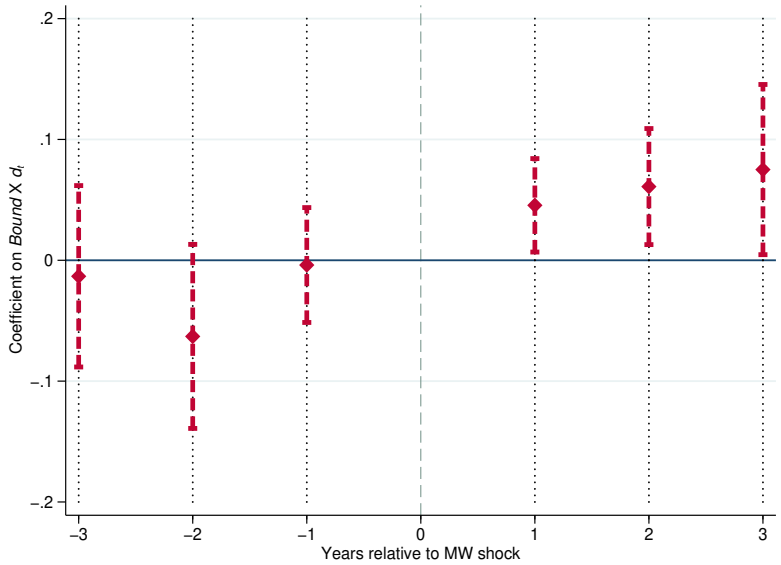
Pairolero, N. A., Giczy, A. V., Torres, G., Islam Erana, T., Finlayson, M. A., Toole, A. A., 2025. The artificial intelligence patent dataset (AIPD) 2023 update. Journal of Technology Transfer .

Whited, T. M., Wu, G., 2006. Financial constraints risk. Review of Financial Studies 19, 531–559.

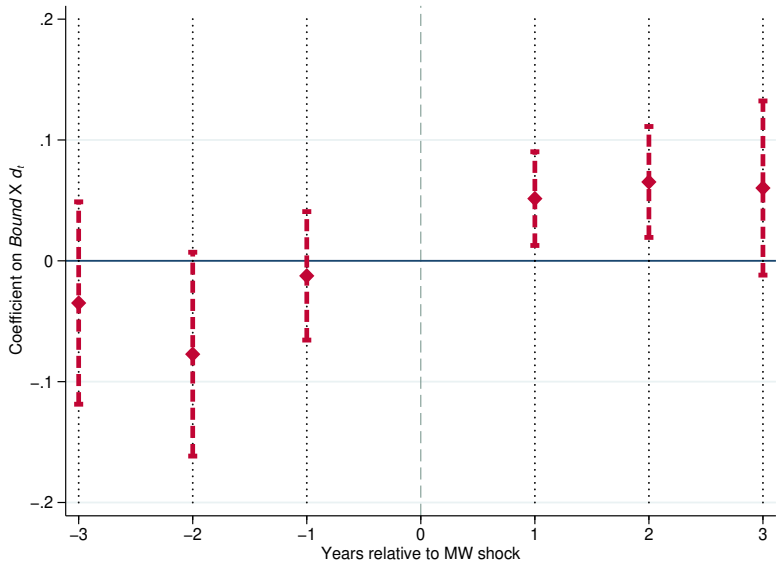
Zeira, J., 1998. Workers, machines, and economic growth. Quarterly Journal of Economics 113, 1091–1117.

Figure I: Labor Cost Induced Innovation: Dynamic Effect Using Federal Minimum Wage Shocks

(a) *Num Patents*



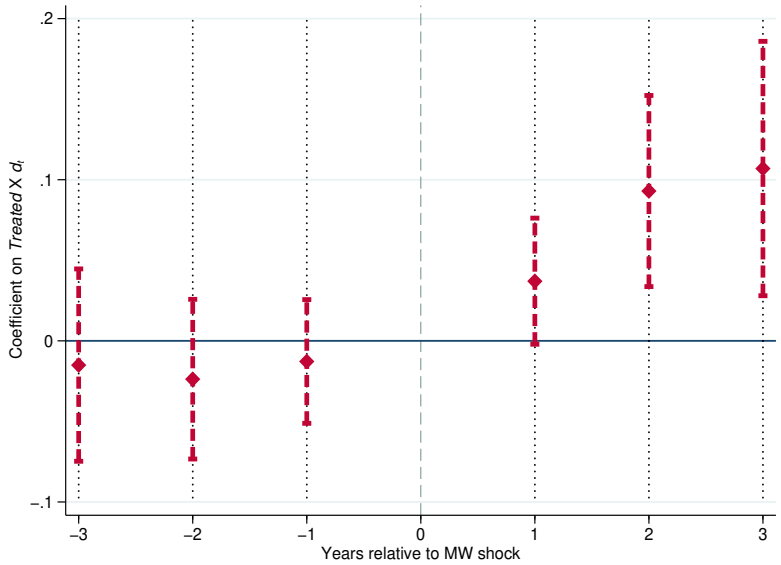
(b) *Num Citations*



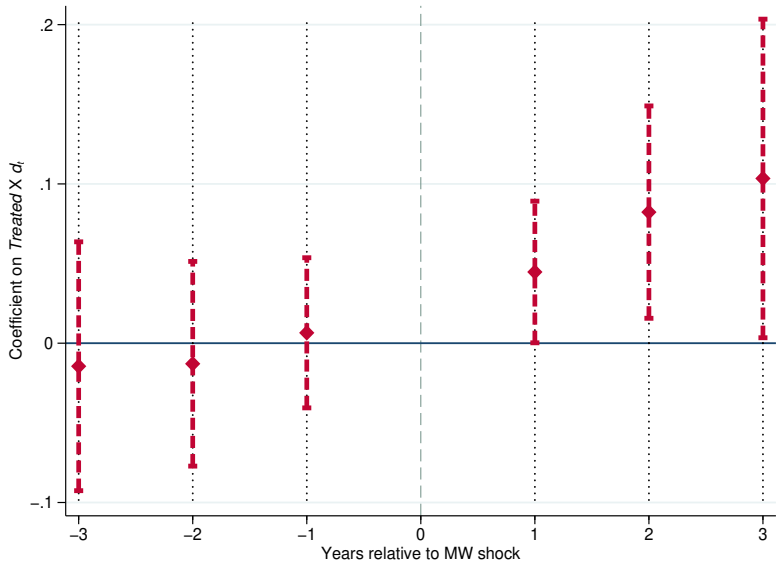
The figures show the dynamics of corporate innovation around the first effective date for each cluster of federal minimum wage increases. We replace $Post^{fed}$ in Equation (2) with year-by-year indicators (d_t) and plot the resulting coefficients on the interaction between *Bound* and d_t relative to the federal minimum wage shock, with 95% confidence intervals. The dependent variable is *Num Patents* in panel (a) and *Num Citations* in panel (b). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). *Bound* is an indicator variable set to one if a firm in a given year is headquartered in a state whose minimum wage is less than or equal to the federal minimum wage, and zero otherwise. We include firm and industry-by-year fixed effects and lagged firm- and state-level control variables. All variables are defined in Appendix Table A1.

Figure II: Labor Cost Induced Innovation: Dynamic Effects Using Stacked Difference-in-Differences

(a) *Num Patents*



(b) *Num Citations*



The figures show the dynamics of corporate innovation around large increases in state minimum wage. We replace $Post_{st}$ in Equation (3) with year-by-year indicators (d_t) and plot the resulting coefficients on the interaction between *Treated* and d_t relative to the state-level minimum wage shock, with 95% confidence intervals. The dependent variable is *Num Patents* in panel (a) and *Num Citations* in panel (b). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). *Treated* is an indicator variable set to one if a firm in a given year is headquartered in a state whose minimum wage increase exceeds three times the inflation rate, and zero otherwise. To identify clean controls, we restrict candidates to firms that remain untreated throughout [-5, +3] window around the event year. We include cohort-specific firm and industry-by-year fixed effects and lagged firm- and state-level control variables. All variables are defined in Appendix Table A1.

Table I: Descriptive Statistics

The table provides descriptive statistics of the main variables used in this study. The sample spans the period 1985-2021. It includes all non-financial and non-utility firms headquartered in the U.S. that filed at least one patent with the USPTO during the sample period. All variables are defined in Appendix Table A1.

	Mean	Std.Dev.	P10	Median	P90	# of Obs.
Num Patents	16.574	52.071	0.000	1.000	37.000	51,129
Num Citations	15.770	48.656	0.000	1.000	35.886	51,129
Min Wage	6.026	2.112	3.350	5.150	8.700	51,129
ln(M/B)	0.473	0.743	-0.388	0.380	1.511	51,129
ln(*Assets*)	5.408	2.205	2.689	5.202	8.481	51,129
Leverage	0.181	0.196	0.000	0.132	0.435	51,129
Profitability	0.010	0.290	-0.333	0.099	0.224	51,129
Tangibility	0.201	0.162	0.035	0.160	0.423	51,129
R&D	0.111	0.159	0.005	0.057	0.271	51,129
State GDP Growth	2.740	2.618	-0.200	2.800	6.000	51,129
ln(*State Population*)	16.222	0.881	15.096	16.246	17.400	51,129
State Unemp Rate	5.992	1.931	3.900	5.500	8.800	51,129
Ratio of AI Patent (50%)	0.153	0.280	0.000	0.000	0.600	31,853
Ratio of AI Patent (86%)	0.112	0.244	0.000	0.000	0.455	31,853
Ratio of AI Patent (93%)	0.107	0.238	0.000	0.000	0.417	31,853
Ratio of AUTO-AI Patent (50%)	0.134	0.260	0.000	0.000	0.500	31,853
Ratio of AUTO-AI Patent (86%)	0.098	0.225	0.000	0.000	0.354	31,853
Ratio of AUTO-AI Patent (93%)	0.093	0.219	0.000	0.000	0.333	31,853
Innov Eff	0.126	0.498	0.000	0.023	0.263	49,093
ln(*Employees*)	-0.027	2.169	-2.718	-0.165	2.976	50,725
ln(*Capital-Labor Ratio*)	3.938	1.024	2.730	3.909	5.195	50,647
Tobin's q	2.420	2.108	0.963	1.712	4.707	51,084
ln(*Sales/Employees*)	5.638	0.806	4.829	5.675	6.495	49,824

Table II: The Impact of Labor Cost Shocks on Corporate Innovation

The table reports fixed effects Poisson regressions of corporate innovation on the minimum wage (*Min Wage*), defined as the statutory rate in the state where the firm is headquartered. The dependent variable is *Num Patents* in columns (1)-(4) and *Num Citations* in columns (5)-(8). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In columns (3)-(4) and (7)-(8), we include lagged firm- and state-level control variables. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Num Patents				*Num Citations*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Min Wage	0.082***	0.070***	0.035*	0.036**	0.114***	0.085***	0.075**	0.055**
	(0.027)	(0.019)	(0.021)	(0.017)	(0.040)	(0.025)	(0.030)	(0.023)
ln(*M/B*)			0.131***	0.136***			0.141***	0.158***
			(0.031)	(0.030)			(0.028)	(0.023)
ln(*Assets*)			0.502***	0.508***			0.512***	0.511***
			(0.022)	(0.034)			(0.024)	(0.039)
Leverage			-0.243***	-0.309***			-0.201**	-0.288***
			(0.094)	(0.096)			(0.079)	(0.085)
Profitability			0.121	0.028			0.178	0.083
			(0.140)	(0.068)			(0.150)	(0.072)
Tangibility			0.254	0.132			0.323*	0.199
			(0.184)	(0.133)			(0.177)	(0.145)
R&D			1.176***	1.092***			1.283***	1.171***
			(0.147)	(0.111)			(0.144)	(0.094)
State GDP Growth			-0.010**	-0.012***			-0.006	-0.010***
			(0.004)	(0.004)			(0.004)	(0.004)
ln(*State Population*)			0.003	-0.081**			0.004	-0.085**
			(0.036)	(0.039)			(0.048)	(0.041)
State Unemp Rate			-0.002	0.011			-0.002	0.008
			(0.011)	(0.012)			(0.010)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
# of Obs.	69,098	67,955	51,129	50,311	67,237	65,850	49,910	49,020
Pseudo R^2	0.861	0.874	0.873	0.883	0.846	0.862	0.859	0.871

Table III: Labor Cost Induced Innovation: Using Federal Minimum Wage Shocks

The table presents fixed effects Poisson regressions for the difference-in-difference model in Equation (2). The dependent variable is *Num Patents* in columns (1)-(2) and *Num Citations* in columns (3)-(4). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). The explanatory variable of interest is the interaction between *Bound* and $Post^{fed}$. *Bound* is an indicator variable set to one if a firm in a given year is headquartered in a state whose minimum wage is less than or equal to the federal minimum wage, and zero otherwise. $Post^{fed}$ is another indicator that is equal to one for years following an increase in the federal minimum wage. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
$Bound \times Post^{fed}$	0.047*	0.071**	0.052*	0.080***
	(0.027)	(0.028)	(0.028)	(0.031)
Bound	0.002	-0.058*	0.013	-0.056
	(0.052)	(0.035)	(0.059)	(0.038)
$Post^{fed}$	-0.059	-0.027	-0.038	-0.011
	(0.053)	(0.055)	(0.047)	(0.054)
$\ln(M/B)$	0.159***	0.157***	0.171***	0.171***
	(0.026)	(0.027)	(0.029)	(0.028)
$\ln(Assets)$	0.609***	0.576***	0.584***	0.547***
	(0.042)	(0.031)	(0.036)	(0.028)
Leverage	-0.424***	-0.457***	-0.383**	-0.399***
	(0.153)	(0.113)	(0.155)	(0.110)
Profitability	-0.022	-0.036	-0.063	-0.037
	(0.192)	(0.130)	(0.162)	(0.106)
Tangibility	0.351	0.195	0.401	0.196
	(0.283)	(0.344)	(0.347)	(0.409)
R&D	1.291***	1.266***	1.122***	1.156***
	(0.331)	(0.252)	(0.338)	(0.241)
State GDP Growth	-0.001	-0.005	0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)
$\ln(State\ Population)$	0.013	-0.078	0.017	-0.085
	(0.054)	(0.054)	(0.061)	(0.057)
State Unemp Rate	0.021	0.032*	0.020	0.031*
	(0.016)	(0.017)	(0.017)	(0.019)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	25,671	25,236	25,529	25,092
Pseudo R^2	0.866	0.875	0.861	0.871

Table IV: Labor Cost Induced Innovation: Using Stacked Difference-in-Differences

The table reports fixed effects Poisson regressions for the stacked difference-in-difference model in Equation (3). We stack all event-specific observations within the 7-year event window [-3, +3] by aligning minimum wage increases in event time. The dependent variable is *Num Patents* in columns (1)-(2) and *Num Citations* in columns (3)-(4). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). The explanatory variable of interest is the interaction between *Treated* and $Post_{st}$. *Treated* is an indicator variable set to one if a firm in a given year is headquartered in a state whose minimum wage increase exceeds three times the inflation rate, and zero otherwise. To identify clean controls, we restrict candidates to firms that remain untreated throughout [-5, +3] window around the event year. $Post_{st}$ is another indicator that is equal to one for years following an increase in the minimum wage. Odd-numbered columns include cohort-specific firm and year fixed effects, while even-numbered columns include cohort-specific firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
$Treated \times Post_{st}$	0.090***	0.080***	0.082***	0.073***
	(0.023)	(0.028)	(0.022)	(0.027)
ln(M/B)	0.041	0.082**	0.035	0.075**
	(0.036)	(0.033)	(0.038)	(0.037)
ln(*Assets*)	0.429***	0.463***	0.425***	0.455***
	(0.061)	(0.069)	(0.062)	(0.069)
Leverage	-0.291***	-0.240**	-0.284***	-0.250**
	(0.087)	(0.100)	(0.093)	(0.115)
Profitability	0.147	0.157	0.171	0.188
	(0.120)	(0.104)	(0.138)	(0.120)
Tangibility	0.243*	0.396**	0.174	0.307
	(0.145)	(0.193)	(0.152)	(0.205)
R&D	1.182***	1.191***	1.278***	1.289***
	(0.334)	(0.363)	(0.334)	(0.362)
State GDP Growth	0.001	0.003	0.004	0.007
	(0.003)	(0.005)	(0.004)	(0.005)
ln(*State Population*)	-0.045	-0.062	-0.062	-0.067
	(0.051)	(0.050)	(0.053)	(0.051)
State Unemp Rate	0.008	0.017**	0.012	0.022**
	(0.008)	(0.009)	(0.009)	(0.009)
Cohort Firm FE	Yes	Yes	Yes	Yes
Cohort Year FE	Yes	No	Yes	No
Cohort Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	66,423	62,983	65,397	61,960
Pseudo R^2	0.887	0.891	0.880	0.884

Table V: Labor Cost Induced Innovation: The Role of Financial Flexibility

The tables report fixed effects Poisson regressions of corporate innovation on the minimum wage (*Min Wage*) interacted with an indicator of financial flexibility (*FF*). The dependent variable is *Num Patents* in columns (1)-(2) and *Num Citations* in columns (3)-(4). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). *Min Wage* is the statutory rate in the state where the firm is headquartered. In Panel A, FF_{HP} is set to one if a firm's *HP Index* is in the bottom tercile in a given year, and zero if in the top tercile. In Panel B, FF_{KZ} is defined analogously using *KZ Index*. Construction details are provided in Appendix Table A1. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with each *FF* indicator. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. HP Index

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
Min Wage × FF_{HP}	0.088***	0.063***	0.105***	0.081**
	(0.023)	(0.024)	(0.027)	(0.033)
Min Wage	-0.058**	-0.033	-0.034	-0.037
	(0.025)	(0.031)	(0.030)	(0.036)
FF_{HP}	-2.006	-0.952	-4.317***	-3.269**
	(1.353)	(1.352)	(1.397)	(1.332)
Firm and State Controls, Controls × FF_{HP}	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	31,423	30,788	30,581	29,885
Pseudo R^2	0.890	0.901	0.877	0.890

Panel B. KZ Index

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
Min Wage × FF_{KZ}	0.041**	0.014	0.081***	0.051**
	(0.019)	(0.021)	(0.017)	(0.023)
Min Wage	-0.018	0.005	-0.036	-0.028
	(0.024)	(0.026)	(0.028)	(0.031)
FF_{KZ}	0.475	1.136	0.989	1.918*
	(0.832)	(1.052)	(0.753)	(0.984)
Firm and State Controls, Controls × FF_{KZ}	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	28,245	27,582	27,481	26,794
Pseudo R^2	0.880	0.889	0.864	0.875

Table V: Labor Cost Induced Innovation: The Role of Financial Flexibility (continued)

The tables report fixed effects Poisson regressions of corporate innovation on the minimum wage (*Min Wage*) interacted with an indicator of financial flexibility (*FF*). The dependent variable is *Num Patents* in columns (1)-(2) and *Num Citations* in columns (3)-(4). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). *Min Wage* is the statutory rate in the state where the firm is headquartered. In Panel C, FF_{WW} is set to one if a firm's *WW Index* is in the bottom tercile in a given year, and zero if in the top tercile. In Panel D, FF_{DIV} is set to one if a firm pays dividends on common stock, and zero otherwise. Construction details are provided in Appendix Table A1. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with each *FF* indicator. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel C. WW Index

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
Min Wage × FF_{WW}	0.072***	0.040*	0.096***	0.054*
	(0.011)	(0.022)	(0.015)	(0.030)
Min Wage	-0.032	-0.003	-0.007	0.004
	(0.025)	(0.030)	(0.032)	(0.036)
FF_{WW}	0.255	-0.153	-0.629	-0.563
	(0.823)	(0.716)	(0.705)	(0.564)
Firm and State Controls, Controls × FF_{WW}	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	30,197	29,560	29,593	28,906
Pseudo R^2	0.885	0.896	0.874	0.887

Panel D. Dividend

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
Min Wage × FF_{DIV}	0.036*	0.041**	0.027	0.044**
	(0.022)	(0.018)	(0.026)	(0.018)
Min Wage	0.011	0.010	0.056	0.027
	(0.023)	(0.020)	(0.035)	(0.026)
FF_{DIV}	0.278	1.033*	0.241	0.961*
	(0.569)	(0.565)	(0.540)	(0.533)
Firm and State Controls, Controls × FF_{DIV}	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	48,462	47,658	47,382	46,505
Pseudo R^2	0.876	0.885	0.862	0.873

Table V: Labor Cost Induced Innovation: The Role of Financial Flexibility (continued)

Panel E reports fixed effects Poisson regressions of corporate innovation on the minimum wage (*Min Wage*) interacted with an indicator of financial flexibility (*FF*). The dependent variable is *Num Patents* in columns (1)-(2) and *Num Citations* in columns (3)-(4). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). *Min Wage* is the statutory rate in the state where the firm is headquartered. FF_{PCM} is set to one if a firm's excess price-cost margin is in the top tercile in a given year, and zero if in the bottom tercile. Construction details are provided in Appendix Table A1. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with FF_{DIV}. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel E. Price-Cost Margin

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
Min Wage $\times$ FF_{PCM}	0.067***	0.079***	0.064***	0.086***
	(0.014)	(0.013)	(0.016)	(0.014)
Min Wage	-0.040	-0.048	0.018	-0.014
	(0.028)	(0.031)	(0.035)	(0.033)
FF_{PCM}	0.369	0.776	0.294	0.658
	(0.764)	(0.687)	(0.788)	(0.729)
Firm and State Controls, Controls $\times$ FF_{PCM}	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	28,176	27,371	27,633	26,739
Pseudo R^2	0.893	0.901	0.880	0.891

Table VI: Labor Cost Induced Innovation for Minimum Wage Sensitive Industries

The tables report fixed effects Poisson regressions of corporate innovation on the minimum wage (*Min Wage*) interacted with an indicator for minimum wage sensitive industries (*MW Ind*). The dependent variable is *Num Patents* in columns (1)-(2) and *Num Citations* in columns (3)-(4). *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted. *Num Citations* is the number of *adjusted* forward citations to those patents where each patent's citation count is divided by the average citations of patents in the same first-listed CPC class and the same filing year (Hall et al., 2001). *Min Wage* is the statutory rate in the state where the firm is headquartered. *MW Ind* is set to one if a firm's primary industry is among those most exposed to minimum wages (i.e., industries with an above-median share of hourly workers earning at or below the federal minimum wage), and zero otherwise. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with *MW Ind*. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Num Patents		*Num Citations*	
	(1)	(2)	(3)	(4)
Min Wage × *MW Ind*	0.044*	0.042*	0.087***	0.076***
	(0.023)	(0.021)	(0.026)	(0.025)
Min Wage	0.027	0.009	0.056**	0.026
	(0.020)	(0.044)	(0.028)	(0.063)
MW Ind	-0.392	-2.109*	-0.126	-2.586**
	(1.506)	(1.102)	(1.421)	(1.205)
ln(*M/B*)	0.138***	0.139***	0.145***	0.149***
	(0.037)	(0.047)	(0.036)	(0.044)
ln(*Assets*)	0.486***	0.458***	0.491***	0.445***
	(0.026)	(0.028)	(0.028)	(0.029)
Leverage	-0.206**	-0.271***	-0.196**	-0.274***
	(0.088)	(0.100)	(0.081)	(0.094)
Profitability	0.142	0.108	0.217	0.129
	(0.174)	(0.151)	(0.182)	(0.155)
Tangibility	0.303*	0.137	0.359**	0.188
	(0.183)	(0.216)	(0.166)	(0.218)
R&D	1.157***	1.121***	1.322***	1.179***
	(0.131)	(0.136)	(0.148)	(0.133)
State GDP Growth	-0.009*	0.015	-0.004	-0.001
	(0.005)	(0.052)	(0.005)	(0.051)
ln(*State Population*)	-0.004	-0.012	0.003	-0.045
	(0.040)	(0.107)	(0.052)	(0.127)
State Unemp Rate	-0.003	-0.010	-0.002	-0.021
	(0.011)	(0.040)	(0.010)	(0.041)
Controls × *MW Ind*	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State-by-Year FE	No	Yes	No	Yes
# of Obs.	51,129	50,851	49,910	49,605
Pseudo R^2	0.874	0.884	0.860	0.871

Table VII: The Impact of Labor Cost Shocks on AI-Related Innovation

Panel A reports fixed effect OLS regressions of the ratio of a firm's AI-related patent applications (*Ratio of AI Patent*) on the minimum wage (*Min Wage*) interacted with an indicator for minimum wage sensitive industries (*MW Ind*). The dependent variable, *Ratio of AI Patent*, is the fraction of a firm's AI-related patent applications filed in a year that are ultimately granted, following Pairolero et al. (2025). AI relevance is determined using probability thresholds of 50%, 86%, or 93%. *Min Wage* is defined as the statutory rate in the state where the firm is headquartered. *MW Ind* is set to one if a firm's primary industry is among those most exposed to minimum wages—industries with an above-median share of hourly workers earning at or below the federal minimum wage—, and zero otherwise. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with *MW Ind*. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. AI Patent Ratios

	Ratio of AI Patent (50%)		*Ratio of AI Patent* (86%)		*Ratio of AI Patent* (93%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Min Wage×*MW Ind*	2.352***	2.235***	2.241***	2.117**	2.097***	1.986**
	(0.618)	(0.707)	(0.698)	(0.792)	(0.710)	(0.802)
Min Wage	-0.080	-1.424*	0.059	-0.467	0.080	-0.446
	(0.286)	(0.760)	(0.270)	(0.821)	(0.277)	(0.786)
MW Ind	5.219	4.113	-8.727	-4.300	-10.114	-4.700
	(21.714)	(26.882)	(18.340)	(21.427)	(17.595)	(20.891)
ln(*M*/*B*)	0.215	0.296	0.230	0.413	0.185	0.366
	(0.289)	(0.284)	(0.250)	(0.259)	(0.245)	(0.249)
ln(*Assets*)	-0.301	-0.243	-0.072	-0.006	-0.072	-0.004
	(0.251)	(0.245)	(0.220)	(0.202)	(0.216)	(0.189)
Leverage	0.569	0.710	0.757	0.871	0.781	0.886
	(0.880)	(0.904)	(0.694)	(0.673)	(0.659)	(0.638)
Profitability	-1.821	-1.306	-1.938**	-1.715**	-1.642*	-1.438
	(1.322)	(1.445)	(0.794)	(0.847)	(0.838)	(0.895)
Tangibility	0.872	-0.345	1.102	0.545	1.035	0.510
	(1.363)	(1.306)	(1.052)	(1.006)	(1.044)	(1.002)
R&D	-5.197***	-3.989***	-3.933***	-3.137***	-3.606***	-2.766***
	(1.562)	(1.438)	(1.284)	(1.147)	(1.118)	(1.017)
State GDP Growth	-0.022	0.602	-0.123**	0.052	-0.115**	0.211
	(0.074)	(0.481)	(0.048)	(0.215)	(0.047)	(0.178)
ln(*State Population*)	0.644	1.642	0.641	1.645	0.633	1.416
	(0.605)	(1.317)	(0.476)	(1.062)	(0.457)	(1.049)
State Unemp Rate	-0.248	-0.905	-0.253	-1.383*	-0.246	-1.243*
	(0.191)	(0.863)	(0.177)	(0.694)	(0.174)	(0.676)
Controls × *MW Ind*	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
State-by-Year FE	No	Yes	No	Yes	No	Yes
# of Obs.	31,130	30,942	31,130	30,942	31,130	30,942
Adjusted R^2	0.665	0.667	0.663	0.665	0.660	0.662

Table VII: The Impact of Labor Cost Shocks on AI-Related Innovation (continued)

Panel B reports fixed effect OLS regressions of the ratio of a firm's automation-related AI patent applications (*Ratio of AUTO-AI Patent*) on the minimum wage (*Min Wage*) interacted with an indicator for minimum wage sensitive industries (*MW Ind*). The dependent variable, *Ratio of AUTO-AI Patent*, is the fraction of a firm's automation-related AI patent applications filed in a year that are ultimately granted, following Pairolero et al. (2025). Automation-related AI relevance is determined using probability thresholds of 50%, 86%, or 93%. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with *MW Ind*. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel B. Automation-Related AI Patent Ratios

	Ratio of AUTO-AI Patent (50%)		*Ratio of AUTO-AI Patent* (86%)		*Ratio of AUTO-AI Patent* (93%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Min Wage×*MW Ind*	2.188***	2.078**	2.202**	2.091**	2.085**	1.986**
	(0.697)	(0.785)	(0.828)	(0.926)	(0.825)	(0.917)
Min Wage	0.059	-0.812	0.168	0.134	0.209	0.588
	(0.292)	(0.763)	(0.280)	(0.918)	(0.285)	(0.629)
MW Ind	-0.513	5.633	-17.807	-8.440	-16.306	-7.929
	(26.805)	(33.856)	(17.478)	(22.174)	(16.461)	(20.845)
ln(*M*/*B*)	-0.045	0.029	0.044	0.200	-0.014	0.137
	(0.287)	(0.282)	(0.256)	(0.273)	(0.247)	(0.258)
ln(*Assets*)	-0.328	-0.299	-0.070	-0.003	-0.073	-0.020
	(0.278)	(0.273)	(0.222)	(0.201)	(0.219)	(0.190)
Leverage	0.743	0.972	0.649	0.800	0.789	0.916
	(0.958)	(0.941)	(0.732)	(0.737)	(0.685)	(0.686)
Profitability	-0.851	-0.384	-1.443**	-1.216	-1.232*	-1.032
	(1.166)	(1.308)	(0.707)	(0.806)	(0.711)	(0.804)
Tangibility	0.391	-0.325	0.342	-0.027	0.419	-0.047
	(1.394)	(1.363)	(1.089)	(1.016)	(1.063)	(0.937)
R&D	-3.952**	-2.984*	-3.353***	-2.564**	-3.117***	-2.314**
	(1.651)	(1.629)	(1.236)	(1.083)	(1.080)	(0.958)
State GDP Growth	-0.045	0.509	-0.130***	-0.175	-0.106**	-0.061
	(0.062)	(0.526)	(0.042)	(0.278)	(0.047)	(0.247)
ln(*State Population*)	0.574	1.120	0.575	0.917	0.607	0.836
	(0.510)	(1.102)	(0.424)	(0.944)	(0.430)	(0.953)
State Unemp Rate	-0.239*	-0.892	-0.221	-1.177*	-0.224	-1.213*
	(0.139)	(0.764)	(0.165)	(0.651)	(0.160)	(0.673)
Controls × *MW Ind*	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
State-by-Year FE	No	Yes	No	Yes	No	Yes
# of Obs.	31,130	30,942	31,130	30,942	31,130	30,942
Pseudo R^2	0.638	0.640	0.629	0.631	0.626	0.628

Table VIII: The Impact of Labor Cost Shocks on Innovation Input and Efficiency

The table reports regressions of innovation input (*R&D*) and efficiency (*Innov Eff*) on the minimum wage (*Min Wage*) interacted with an indicator for minimum wage sensitive industries (*MW Ind*). The dependent variable is *R&D* in columns (1)-(2) and *Innov Eff* in columns (3)-(4), estimated by fixed effect OLS and fixed effects Poisson regressions, respectively. *R&D* is the annual R&D expenses scaled by the total assets. *Innov Eff* is the ratio of *Num Patents* to *R&D Stock* where *Num Patents* is the number of a firm's patent applications filed in a given year that are ultimately granted, and *R&D Stock* is constructed via the perpetual-inventory method with a 15% knowledge depreciation rate. *Min Wage* is the statutory rate in the state where the firm is headquartered. *MW Ind* is set to one if a firm's primary industry is among those most exposed to minimum wages—industries with an above-median share of hourly workers earning at or below the federal minimum wage—, and zero otherwise. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables and their interactions with *MW Ind*. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	R&D		*Innov Eff*	
	(1)	(2)	(3)	(4)
Min Wage×*MW Ind*	0.004***	0.004***	0.272***	0.234***
	(0.001)	(0.001)	(0.053)	(0.057)
Min Wage	-0.003**	-0.002	-0.052	0.068
	(0.001)	(0.003)	(0.064)	(0.138)
MW Ind	0.046	0.078	0.519	1.308
	(0.079)	(0.082)	(3.100)	(3.787)
ln(*M/B*)	0.002	0.002	0.244***	0.251***
	(0.002)	(0.002)	(0.050)	(0.050)
ln(*Assets*)	-0.010***	-0.010***	-0.060	-0.061
	(0.002)	(0.002)	(0.064)	(0.073)
Leverage	-0.029***	-0.028***	-0.208	-0.435**
	(0.008)	(0.008)	(0.146)	(0.177)
Profitability	-0.137***	-0.136***	0.674***	0.574***
	(0.007)	(0.007)	(0.213)	(0.213)
Tangibility	0.016	0.016	-0.167	-0.054
	(0.012)	(0.012)	(0.341)	(0.418)
State GDP Growth	0.001*	0.002	-0.020	-0.054
	(0.000)	(0.003)	(0.013)	(0.076)
ln(*State Population*)	0.008***	0.004	0.092	0.205
	(0.002)	(0.005)	(0.101)	(0.215)
State Unemp Rate	0.001	0.004	-0.035	-0.138
	(0.001)	(0.004)	(0.031)	(0.171)
Controls × *MW Ind*	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State-by-Year FE	No	Yes	No	Yes
# of Obs.	53,498	53,381	54,753	54,477
Adjusted / Pseudo R^2	0.713	0.710	0.490	0.534

Table IX: Innovation Ability and the Effect of Labor Cost Shocks on Employment and Capital Intensity

The table reports fixed effect OLS regressions of employment (*Employees*) and capital intensity (*Capital-Labor Ratio*) on the minimum wage (*Min Wage*) interacted with the stock of R&D (*R&D Stock*). The dependent variable is ln(*Employees*) in columns (1)-(2) and ln(*Capital-Labor Ratio*) in columns (3)-(4). ln(*Employees*) is the logarithm of the number of employees, and ln(*Capital-Labor Ratio*) is the logarithm of the ratio of property, plant, and equipment to the number of employees. *Min Wage* is the statutory rate in the state where the firm is headquartered. ln(1+*R&D Stock*) is the logarithm of *R&D Stock*, constructed via the perpetual-inventory method with a 15% knowledge depreciation rate. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	ln(*Employees*)		ln(*Capital-Labor Ratio*)	
	(1)	(2)	(3)	(4)
Min Wage×ln(1+*R&D Stock*)	-0.008***	-0.006***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Min Wage	0.032***	0.022**	-0.042***	-0.044***
	(0.010)	(0.009)	(0.012)	(0.013)
ln(1+*R&D Stock*)	0.094***	0.091***	-0.141***	-0.138***
	(0.011)	(0.013)	(0.009)	(0.010)
ln(*M/B*)	0.155***	0.160***	0.035***	0.027**
	(0.009)	(0.008)	(0.009)	(0.011)
ln(*Assets*)	0.676***	0.672***	0.298***	0.307***
	(0.008)	(0.008)	(0.019)	(0.018)
Leverage	-0.114***	-0.102***	-0.127***	-0.153***
	(0.027)	(0.024)	(0.036)	(0.030)
Profitability	0.158***	0.156***	-0.007	-0.016
	(0.026)	(0.026)	(0.031)	(0.030)
Tangibility	0.636***	0.642***	3.180***	3.229***
	(0.090)	(0.064)	(0.129)	(0.130)
R&D	0.660***	0.650***	-0.107	-0.109
	(0.065)	(0.070)	(0.103)	(0.099)
CAPEX	-0.024***	-0.018***	0.136***	0.129***
	(0.005)	(0.006)	(0.007)	(0.008)
Cash	-0.512***	-0.509***	0.378***	0.381***
	(0.039)	(0.029)	(0.037)	(0.032)
Sales Growth	0.018***	0.019***	-0.017***	-0.014***
	(0.005)	(0.005)	(0.004)	(0.004)
Past Returns	-0.005***	-0.006***	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Past Volatility	-0.462***	-0.347***	0.151*	-0.016
	(0.088)	(0.086)	(0.076)	(0.067)
State GDP Growth	-0.000	-0.000	0.000	0.001
	(0.001)	(0.002)	(0.002)	(0.002)
ln(*State Population*)	0.024*	0.018	-0.020	-0.006
	(0.013)	(0.012)	(0.016)	(0.017)
State Unemp Rate	0.002	0.000	-0.004	-0.004
	(0.006)	(0.006)	(0.007)	(0.007)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes
# of Obs.	45,204	44,981	45,172	44,949
Adjusted R^2	0.974	0.975	0.849	0.855

Table X: Innovation Ability and the Effect of Labor Cost Shocks on Firm Value, Profitability, and Labor Productivity

The table reports fixed effect OLS regressions of firm performance on the minimum wage (*Min Wage*) interacted with the stock of knowledge (*R&D Stock*). The dependent variable is *Tobin's q* in columns (1)-(2), *Protitability* in columns (3)-(4), and ln(*Sales/Employees*) in columns (5)-(6). *Tobin's q* is the ratio of the market value of assets to the book value of assets. *Protitability* is operating income before depreciation normalized by the total assets. ln(*Sales/Employees*) is the logarithm of the ratio of sales to the number of employees. *Min Wage* is the statutory rate in the state where the firm is headquartered. ln(1+*R&D Stock*) is the logarithm of *R&D Stock*, constructed via the perpetual-inventory method with a 15% knowledge depreciation rate. Odd-numbered columns include firm and year fixed effects, while even-numbered columns include firm and industry-by-year fixed effects. In all columns, we include lagged firm- and state-level control variables. All variables are defined in Appendix Table A1. The standard errors in parentheses are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Tobin's q		*Protitability*		ln(*Sales/Employees*)	
	(1)	(2)	(3)	(4)	(5)	(6)
Min Wage×ln(1+*R&D Stock*)	0.012**	0.016***	0.065***	0.067**	0.004***	0.004***
	(0.005)	(0.006)	(0.020)	(0.030)	(0.001)	(0.001)
Min Wage	-0.048**	-0.084***	0.017	-0.042	0.005	0.003
	(0.020)	(0.022)	(0.161)	(0.197)	(0.011)	(0.010)
ln(1+*R&D Stock*)	-0.037	-0.037	-0.935***	-0.865***	-0.008	-0.001
	(0.045)	(0.050)	(0.229)	(0.243)	(0.011)	(0.012)
ln(*M/B*)	1.183***	1.176***	2.292***	2.333***	0.011	0.011
	(0.029)	(0.034)	(0.241)	(0.261)	(0.011)	(0.014)
ln(*Assets*)	-0.368***	-0.379***	-0.176	-0.178	0.036***	0.030***
	(0.020)	(0.023)	(0.203)	(0.234)	(0.008)	(0.007)
Leverage	0.218***	0.216***	3.130***	3.029***	0.144***	0.141***
	(0.073)	(0.070)	(0.925)	(0.941)	(0.038)	(0.034)
Profitability	-0.464***	-0.474***	46.243***	45.845***	0.635***	0.633***
	(0.097)	(0.098)	(1.391)	(1.562)	(0.062)	(0.065)
Tangibility	-0.061	-0.035	4.047*	4.128**	-0.446***	-0.461***
	(0.177)	(0.226)	(2.082)	(1.959)	(0.097)	(0.086)
R&D	1.123***	0.993***	5.600***	5.234**	0.311***	0.288***
	(0.145)	(0.132)	(1.855)	(2.127)	(0.106)	(0.102)
CAPEX	-0.064**	-0.050	-0.961***	-0.861***	-0.036**	-0.037***
	(0.028)	(0.030)	(0.200)	(0.204)	(0.014)	(0.012)
Cash	0.248**	0.248**	-11.718***	-11.697***	-0.427***	-0.427***
	(0.105)	(0.094)	(1.092)	(1.086)	(0.037)	(0.037)
Sales Growth	0.033	0.038*	-1.015***	-0.972***	0.059***	0.058***
	(0.021)	(0.022)	(0.177)	(0.169)	(0.009)	(0.009)
Past Returns	0.028**	0.029**	0.238***	0.234***	0.008***	0.009***
	(0.011)	(0.011)	(0.020)	(0.023)	(0.002)	(0.002)
Past Volatility	-0.366*	-0.357	-7.378**	-8.604***	-0.071	-0.239***
	(0.206)	(0.230)	(2.793)	(2.652)	(0.096)	(0.076)
State GDP Growth	0.002	0.001	-0.148*	-0.134*	0.001	0.001
	(0.006)	(0.007)	(0.075)	(0.070)	(0.002)	(0.002)
ln(*State Population*)	-0.014	-0.021	-0.581	-0.501	-0.024	-0.018
	(0.031)	(0.032)	(0.387)	(0.399)	(0.018)	(0.018)
State Unemp Rate	0.020***	0.015**	-0.113	-0.113	0.004	0.003
	(0.007)	(0.006)	(0.119)	(0.125)	(0.004)	(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes	No	Yes
# of Obs.	45,513	45,295	45,522	45,303	44,969	44,742
Adjusted R^2	0.595	0.601	0.741	0.740	0.718	0.724

Appendix

Table A1: Variable Definitions

Variable	Definition
Num Patents	The number of a firm's patent applications filed in a year that are ultimately granted.
Num Citations	The number of *adjusted* forward citations to a firm's patents filed in a year that are ultimately granted. Following Hall et al. (2001) and Atanassov (2013), each patent's citation count is divided by the average citations of patents in the same first-listed CPC (Cooperative Patent Classification) class and the same filing year.
Min Wage	The effective hourly minimum wage rate calculated as the weighted average hourly minimum wage applicable to a firm based on its headquarters state, where weights reflect the number of days each rate is in effect during the year. Under Section 18 of the Fair Labor Standards Act, the effective rate is the maximum of the state and federal minima. Historical changes are sourced from the Tax Policy Center (compiled from the U.S. Department of Labor's Wage and Hour Division and the *Monthly Labor Review* by the Bureau of Labor Statistics).
Bound	An indicator variable set to one if a firm is headquartered in a bound state, and zero otherwise. A bound state is defined as a state that either lacks its own minimum wage law or sets a minimum wage less than or equal to the federal minimum wage during the period from one year before to three years after the first effective date of each cluster of federal minimum wage changes: (i) the first cluster enacted on November 17, 1989: the federal minimum hourly wage rate effectively increased from \$3.35 to \$3.80 on April 1, 1990, and to \$4.25 on April 1, 1991; (ii) the second cluster enacted on August 20, 1996: the federal minimum hourly wage rate effectively increased from \$4.25 to \$4.75 on October 1, 1996, and to \$5.15 on September 1, 1997; (iii) the third cluster enacted on May 25, 2007: the rate effectively increased from \$5.15 to \$5.85 on July 24, 2007, to \$6.55 on July 24, 2008, and to \$7.25 on July 24, 2009.
$Post^{fed}$	An indicator variable set to one for event years from 1 to 3, and zero otherwise. Event year 1 is a firm's first fiscal year that ends after the first effective date of each cluster of federal minimum wage changes; other event years are defined relative to event year 1.
Treated	An indicator variable set to one if a firm in a given year is headquartered in a state whose minimum wage increase exceeds three times the prior-year inflation rate (measure just before the effective date), and zero otherwise. To identify clean controls, we restrict candidates to firms that remain untreated throughout [-5, +3] window around the event year.
$Post_{st}$	An indicator set to one for years following an increase in the state minimum wage that exceeds three times the prior-year inflation rate, and zero otherwise.
$\ln(M/B)$	The natural logarithm of market value of assets (the sum of the market value of equity [CSHO $\times$ PRCC_F], the book value of long-term debt [DLTT] and the book value of debt in current liabilities [DLC]) normalized by the book value of total assets [AT].
$\ln(Assets)$	The natural logarithm of total assets [AT].

Table A1 (Continued)

Variable	Definition [Compustat designations where appropriate]
Leverage	The sum of long-term debt [DLTT] and debt in current liabilities [DLC] normalized by the total assets [AT].
Profitability	Operating income before depreciation [OIBDP] normalized by the total assets [AT].
Tangibility	Property, plant, and equipment [PPENT] scaled by the total assets [AT]
R&D	Annual R&D expenses [XRD] scaled by the total assets.
CAPEX	Capital expenditures [CAPX] normalized by the beginning-of-the-year capital stock (property, plant, and equipment) [PPENT]
Cash	Cash and equivalent [CHE] divided by the total assets [AT].
Sales Growth	The annual growth rate of sales defined as [SALE/lagged SALE] −1.
Past Returns	The average monthly stock returns over the prior 60 months.
Past Volatility	The standard deviation of monthly stock returns over the prior 60 months.
State GDP Growth	State-level annual growth rate of real GDP from the Bureau of Economic Analysis.
ln(*State Population*)	Log of intercensal estimates of the resident population for each state from the U.S. Census Bureau.
State Unemp Rate	State-level unemployment rate from the Bureau of Labor Statistics.
FF_{HP}	An indicator variable set to one if a firm's *HP Index* is in the bottom tercile (financially flexible/unconstrained) in a year, and zero if in the top tercile (financially constrained). Following Hadlock and Pierce (2010), *HP Index* is defined as $-0.737Size + 0.043Size^2 - 0.040Age$, where *Size* equals the log of inflation-adjusted total assets [AT] (in 2004 dollars), and *Age* is the number of years the firm is listed on Compustat. In calculating the index, we cap *Size* at (the log of) $4.5 billion and *Age* at 37 years.
FF_{KZ}	An indicator variable set to one if a firm's *KZ Index* is in the bottom tercile (financially flexible/unconstrained) in a year, and zero if in the top tercile (financially constrained). Following Lamont et al. (2001), *KZ Index* is defined as −1.001909[(IB + DP) / lagged PPENT] + 0.2826389[(AT + PRCC_F × CSHO −CEQ −TXDB) / AT] + 3.139193[(DLTT + DLC) / (DLTT + DLC + SEQ)] −39.3678[(DVC + DVP) / lagged PPENT] - 1.314759[CHE / lagged PPENT].
FF_{WW}	An indicator variable set to one if a firm's *WW Index* is in the bottom tercile (financially flexible/unconstrained) in a year, and zero if in the top tercile (financially constrained). Following Whited and Wu (2006) and Hennessy and Whited (2007), *WW Index* is defined as −0.091[(IB + DP) / AT] −0.062 [indicator set to one if (DVC + DVP) is positive, and zero otherwise] + 0.021[DLTT / AT] −0.044[log(AT)] + 0.102[average industry *Sales Growth*, estimated separately for each three-digit SIC industry and each year] −0.035[*Sales Growth*].
FF_{DIV}	An indicator variable set to one if a firm pays dividends (financially flexible/unconstrained) on common stock [DVC], and zero (financially constrained) otherwise.

Table A1 (Continued)

Variable	Definition [Compustat designations where appropriate]
FF_{PCM}	An indicator variable set to one if a firm's excess price cost margin, *EPCM*, is in the top tercile (financially flexible/unconstrained) in a year, and zero if in the bottom tercile (financially constrained). Following Gaspar and Massa (2006), *EPCM* is defined as a firm's *PCM* minus the industry value-weighted average *PCM*, where industries are at the three-digit SIC level and weights equal each firm's sales [SALE] share of total industry sales. We compute *PCM* as operating profits (sales [SALE] minus cost of goods sold [COGS] minus selling, general, and administrative expenses [XSGA]) over sales [SALE]. When the numerator components are unavailable (e.g., missing COGS or XSGA), we proxy the numerator with operating income before depreciation [OIBDP].
MW Ind	An indicator variable set to one if a firm's primary industry is among those most exposed to minimum wages, defined as industries with an above-median percentage of hourly workers earning at or below the prevailing federal minimum wage, and zero otherwise. The data are retrieved from the Labor Force Statistics in the Current Population Survey (2017) by the Bureau of Labor Statistics.
ln(1+*R&D Stock*)	A firm's R&D stock constructed via the perpetual-inventory method: starting in 1950, we cumulate annual R&D spending [XRD] with a 15% knowledge depreciation rate.
Ratio of AI Patent	The ratio of a firm's AI (artificial intelligence) related patent applications filed in a year that are ultimately granted to the firm's total patent applications filed in the same year that are ultimately granted. AI relevance for a given patent document is identified with three probability thresholds (50%, 86%, or 93%). Methodological details are in Pairolero et al. (2025).
Ratio of AUTO-AI Patent	The ratio of a firm's automation-related AI patent applications filed in a year that are ultimately granted to the firm's total patent applications filed in the same year that are ultimately granted. Among eight AI component technologies (knowledge processing, speech, AI hardware, evolutionary computation, natural language processing, machine learning, computer vision, and planning/control), AI hardware, machine learning, computer vision, and planning/control are classified as automation-related AI technologies. Automation-related AI relevance for a given patent document is identified with three probability thresholds (50%, 86%, or 93%). Methodological details are in Pairolero et al. (2025).
Innov Eff	The ratio of a firm's *Num Patents* to *R&D Stock*.
ln(*Employees*)	The natural logarithm of the number of employees [EMP].
ln(*Capital-Labor Ratio*)	The natural logarithm of capital-labor ratio defined as property, plant, and equipment [PPENT] divided by the number of employees [EMP].
Tobin's q	The ratio of the market value of assets to the book value of assets [AT] where market value of assets is defined as total assets [AT] plus market equity minus book equity in which market equity is defined as common shares outstanding [CSHO] times fiscal-year closing price [PRCC_F]; book equity is calculated as stockholders' equity [SEQ] minus preferred stock liquidating value [PSTKL] plus balance sheet deferred taxes and investment tax credit [TXDITC] when available minus post-retirement assets [PPROR] when available.
ln(*Sales/Employees*)	The natural logarithm of sales [SALE] divided by the number of employees [EMP].