Regulation-Driven Innovations: A Textual Analysis of U.S. Patents and Federal Regulations*

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Abstract

Some innovations are developed to comply with or circumvent legal and regulatory requirements. While these regulation-driven innovations can generate societal benefits, they may also incur unintended economic costs. This paper explores this unique type of innovation and examines its relationship with firm dynamics, creative destruction, and economic growth. I present a simple Schumpeterian model demonstrating how regulation-driven innovations can serve as a strategy for firms to achieve higher growth, deter competitors, and reduce the rate of creative destruction. Guided by the model's implications, I identify regulation-driven innovations from U.S. patents issued between 1976 and 2020 by measuring the degree of alignment between patents and federal regulations. I construct this measure by estimating textual similarities between patent documents and regulatory texts using natural language processing techniques. Linking the measure with patent- and firm-level data, I find that innovation-regulation alignment is positively associated with the economic value of patents and the growth in size and market power of innovating firms. At the aggregate level, however, the static gains for innovating firms fail to offset the dynamic social costs from reduced reallocation and competition.

Keywords: innovation, regulation, patents, NLP, firm dynamics, creative destruction, economic growth
JEL Codes: C55, E23, E32, O3, O4

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1 Introduction

Innovation is a key driver of economic growth. Researchers and policymakers often focus on market-driven innovations, a significant portion of technological advancements motivated by consumer demand, competition, and market opportunities. However, *regulation-driven innovations*—those developed to comply with or circumvent legal and regulatory requirements—present a unique intersection between public policy and firm strategy. For example, firms develop innovations in emissions-reducing technologies, such as electric vehicles and carbon capture systems, in response to environmental regulations, while public health regulations drive advancements in food safety and drug compliance technologies. As governments implement regulations to address public health, environmental concerns, and market stability, nearly every firm feels the impact, regardless of industry or size. Understanding how firms adapt their innovation activities in response to regulation is crucial. By exploring regulation-driven innovations, we can better understand how regulatory environments shape technological progress and firm dynamics, potentially influencing long-term economic growth.

In this paper, I identify regulation-driven innovations from U.S. patents issued from 1976 to 2020 by measuring the extent to which each patent is aligned with federal regulations based on textual similarities between patent documents and regulatory texts. Drawing on theoretical insights on the Schumpeterian growth model (Aghion and Howitt, 1992), I examine the measure of innovation-regulation alignment at the patent, firm, and macroeconomic levels and study their relationships with firm dynamics, competition, and aggregate economic outcomes. Both theoretical and empirical findings suggest that while regulation-driven innovations can generate private gains for innovating firms, they may negatively impact macroeconomic performance by slowing creative destruction—the process in which new innovations replace and render existing ones obsolete over time (Schumpeter, 1942).

The analysis begins with an extended Schumpeterian model to investigate how regulation-driven innovations could influence business dynamism, firm entry and exit, and creative destruction. I adapt the model from the theoretical framework of Akcigit et al. (2023), which builds on Aghion and Howitt (1992)'s seminal Schumpeterian model formalizing the notion of creative destruction. In the model, firms face a regulatory burden that increases the marginal cost of production. The regulatory burden includes compliance costs with regulatory requirements as well as noncompliance costs such as penalties and litigation fees. However, the firm can adopt a regulation-driven innovation, subject to a fixed cost. The innovation updates the firm's production process, allowing it to produce the same goods with a reduced regulatory burden by complying more efficiently with or circumventing regulatory requirements. The extent of the reduction depends on the degree of alignment between the regulation-driven innovation and the regulations the firm faces.

The model provides implications from both static and dynamic perspectives. In a static setting, adopting a regulation-driven innovation that updates the production process leads to firm growth in its labor input, output, and revenue. Moreover, the growth is larger if the alignment between the innovation and regulations is higher. In a dynamic environment where entrants can displace incumbents with better-quality goods, incumbents' regulation-driven innovations offer them advantages over other market participants who may not have such innovations. This increases barriers to entry, prevents quality-improving innovation, and reduces the rate of creative destruction.

Guided by the model predictions, I present empirical evidence on the economic implications of regulation-driven innovations. I propose a novel measure of innovation-regulation alignment for all U.S. utility patents issued between 1976 and 2020. Inspired by the recent literature that extracts various features of innovations using textual analysis of patent documents (Kelly et al., 2021; Bloom et al., 2021; Kogan et al., 2021; Autor et al., 2024), I construct the measure using natural language processing (NLP) techniques to map patents to the Code of Federal Regulations (CFR). Using a pretrained transformer-based model to generate text embeddings, I estimate the semantic similarity between the text of a patent's abstract and the CFR published before and during the patent's grant year. The measure captures the extent to which the new technology described in a patent aligns with the existing regulations available in the inventor's information set at the time of developing and filing the patent. Regulation-driven innovations are defined as patents with a high degree of alignment with federal regulatory texts.

The patent-level regulatory alignment measure reveals several interesting descriptive patterns. First, both the share of regulation-driven patents and the annual average regulatory alignment value increased over the period of 1976-2020. This trend persists when controlling for the volume of federal regulations. This observation implies that firms may have become more aware of the private value in exploiting regulation through their innovation activities and are increasingly using it as a tool to maintain their market positions. Second, regulation-driven innovations concentrate in several technology classes, including information and communication technology (ICT), technologies for producing and handling chemicals and organisms, refrigeration and heating systems, life-saving and fire-fighting devices, and agriculture. Linking the technology classes with subject areas of the CFR indicates that innovations in these classes are driven by regulations that are widely known to govern relevant firms and industries. These linkages provide additional external validity for the regulatory alignment measure.

Empirical patterns in the patent-level data are consistent with the model implication that regulation-driven innovations tend to bring regulatory advantages and thus additional monopoly rents to innovating firms. By linking the regulatory alignment measure with patent value, I find that a patent's regulatory alignment is positively associated with its private economic value, a measure of the monopoly rents associated with the patent constructed by Kogan et al. (2017). However, the lack of significant relationship between regulatory alignment and scientific value of the patent, as measured by forward citations, suggests that the innovations providing regulatory advantages to firms may differ from those contributing to scientific advance, mirroring the distinction between regulation-driven innovation and quality-improving innovation in the model.

By exploiting the timing of patent grants, I aggregate the measure to identify the extent to which a firm's innovative output was driven by regulation at a given point in time and examine how the firm's regulation-driven innovations relate to its economic performance. Specifically, I match the firm-level measure with Compustat data and estimate the relation between a firm's innovation-regulation alignment and its future growth in firm size and market power. Consistent with the model implications, I find that firms with higher innovation-regulation alignment tend to achieve larger growth in terms of profit, output, capital investment, and employment. In addition, as regulation-driven innovations help firms dominate a market by deterring competitors, I observe a statistically significant positive relationship between a firm's innovation-regulation alignment and growth in its market share and markup.

On the other hand, a firm's regulation-driven innovations create relative disadvantages for its competitors. The empirical analyses on competitors' growth indicate that a firm's innovation-regulation alignment is negatively associated with its competitors' growth in profit, output, and capital. These findings suggest a strong relation between regulatory responses and resource reallocation across firms—a flow to firms with regulation-driven innovations and away from their competitors—and are consistent with the Schumpeterian view of creative destruction.

The patent- and firm-level results suggest that the potential effects of regulation-driven innovation can go beyond private gains (and losses) and have implications for aggregate economic outcomes and growth. To explore the macroeconomic implications, I aggregate the measure of innovation-regulation alignment into a quarterly economy-wide index from 1976 to 2020 and examine its relation with macroeconomic indicators including output, employment, private investment, and stock prices. Using the local projection method (Jordà, 2005), I estimate the impulse responses of the macroeconomic variables to an upward shock in the growth of aggregate innovation-regulation alignment. The estimates suggest that a one-standard-deviation shock leads to a maximum drop of 0.4 percent in GDP, 0.5 percent in employment, 1.6 percent in private domestic investment, and 3.1 percent in the S&P 500 index. The size of these effects is comparable to that of other macroeconomic shocks, such as monetary policy shocks and economic policy uncertainty shocks.

While the analyses in this paper do not aim to establish causal relationships, they provide illustrative evidence of how certain firms can leverage regulation to their advantage through innovation activities. The findings suggest that regulation-driven innovations allow firms to adapt to or exploit regulatory frameworks, potentially enhancing their competitive positions. However, these innovations may also have unintended consequences for the broader economy. As delineated in the Schumpeterian growth model, entrants create new innovations to replace incumbents with old technologies through creative destruction by introducing a better-quality version of an existing product (Aghion and Howitt, 1992). In this process, incumbent firms face incentives to prevent subsequent innovations and slow down creative destruction (Krusell and Rios-Rull, 1996; Mukoyama and Popov, 2014). Similar to other strategies that firms use to achieve this (Baslandze, 2023; Akcigit et al., 2023; Comin and Hobijn, 2009; Argente et al., 2020; Cavenaile et al., 2021), regulation-driven innovations provide another tool for firms to deter competitors and block creative destruction. This, in turn, stifles technological innovation and slows aggregate economic growth.

This paper contributes to our understanding of the complex interplay between regulation and innovation. Traditionally, regulation has been viewed as a burden for businesses, creating compliance costs and diverting resources that could otherwise be used for R&D (Eads, 1980; Aghion et al., 2023; Coffey et al., 2020; Alesina et al., 2018; Garcia-Vega et al., 2021; Samaniego, 2006). Regulation may also discourage or postpone firms' investment and hiring by creating negative perceptions or significant uncertainty about the regulatory environment in which they operate (Baker et al., 2016; Sinclair and Xie, 2022). However, others argue that regulation can also stimulate innovation, particularly with supporting evidence found in the areas of environmental regulations (Porter, 1996; Lanjouw and Mody, 1996; Jaffe and Palmer, 1997) and labor regulations (Acharya et al., 2013, 2014; Bena et al., 2022; Griffith and Macartney, 2014; Manera and Uccioli, 2021; Saint-Paul, 2002). This paper shows that the competing effects of regulation found in the literature are not necessarily contradictory. Some firms may adapt their operations to the regulatory environment and generate private gains, while others continue to suffer from regulatory burden or face higher barriers to entry. As the theory of creative destruction elaborates, there are winners and losers in the process of growth (Baslandze, 2023), and the presence of regulation widens the gap between winners and losers. In aggregate, the dynamic social costs from reduced reallocation and competition may outweigh the static benefits for the winners.

This study also contributes to the broad literature on measuring innovation by creating a new measure that captures the regulatory dimension of innovation. Patents serve as an informative indicator of innovation (Lerner and Seru, 2022; Higham et al., 2021). Prior research has constructed various measures that reflect different aspects of the value of patents (Khanna, 2019). A widely used measure is patent citations, which reflects the technological impact or scientific value of patents (Hall and Trajtenberg, 2005; Higham et al., 2021). However, patents with great scientific value or societal benefits may not be valued equivalently by inventors. Kogan et al. (2017) estimate the private, economic value of patents based on fluctuations in stock prices of publicly-traded firms within a short time window after they were granted a patent. In this paper, I examine how patents' regulatory alignment is associated with both their scientific and economic value.

This study is the first to link patent documents with U.S. federal regulations through an analysis of their semantic textual similarity, extending the recent work that uses textual analysis to extract features of innovation. For example, Kelly et al. (2021) measure the importance of patents based on textual similarity of a given patent to previous and subsequent patents and identify breakthrough innovations since 1840. Bloom et al. (2021) use the full text of patents and earnings conference calls to identify technological innovations that have disrupted a large number of businesses. Other studies (Kogan et al., 2021; Autor et al., 2024; Mann and Püttmann, 2023; Webb, 2019) link patent documents to occupation task descriptions to examine the relationship between technological innovations and labor market outcomes. These studies have demonstrated that text-based measures from patents provide valuable information about innovation and help address many economic questions that are challenging to answer with traditional data.

The remainder of this paper is structured as follows. Section 2 presents a simple Schumpeterian model that illustrates how regulation-driven innovations can influence firm growth and creative destruction. In Section 3, I describe how I construct the empirical measure of patent-level regulatory alignment. Section 4 discusses illustrative examples and descriptive patterns in regulatory alignment of patents, as a way to validate and interpret the measure. Section 5 shows the patent-level analysis, unpacking the relationship between regulatory alignment and value of patents. In Section 6, I present the firm-level measure of innovation-regulation alignment and how it relates to a firm and its competitors' growth. Section 7 explores the macroeconomic implications of innovation-regulation alignment. Section 8 concludes the study.

2 Model

In this section, I adapt the extended Schumpeterian model from Akcigit et al. (2023) to show how regulation-driven innovations affect firm growth and creative destruction. The final goods Y is produced following a constant elasticity of substitution aggregation:

$$Y_t = \frac{1}{1-\psi}\left[\sum_{m=1}^{M} q_{mt}{}^{\frac{\psi}{1-\psi}} y_{mt}\right]^{1-\psi}, \tag{1}$$

where y_m is the amount of intermediate goods of vintage m, and q_m is the quality of vintage m. The price of Y is normalized to 1. The final goods sector is perfectly competitive, and the representative final goods firm chooses the input of vintage m to maximize its profit:

$$\max_{y_{mt}} \frac{1}{1-\psi}\left[\sum_{m=1}^{M} q_{mt}{}^{\frac{\psi}{1-\psi}} y_{mt}\right]^{1-\psi} - p_{mt}y_{mt}. \tag{2}$$

The first order condition leads to the inverse demand function for the producer of vintage m:

$$p_{mt} = q_{mt}^{\frac{\psi}{1-\psi}} \left[\sum_{m=1}^{M} q_{mt}{}^{\frac{\psi}{1-\psi}} y_{mt} \right]^{-\psi}. \tag{3}$$

Different vintages differ by their qualities q_m and are perfect substitutes after adjusting for quality. Following Akcigit et al. (2023), I assume that producers of different vintages compete on prices to win the entire market. In equilibrium, the producer with the highest cost-adjusted quality will become the monopolist of the market and charge the monopoly price. Accordingly, the demand function faced by the producing firm of vintage m becomes:

$$p_{mt} = q_{mt}^{\psi} y_{mt}^{-\psi}. \tag{4}$$

Next, I first study intermediate goods producers in a static environment, where they can choose whether to adopt regulation-driven innovations to update their production process in response to regulation, and then I discuss firm dynamics between entrants and incumbents.

2.1 Static Environment

In a static environment, the producer of intermediate goods m is a monopolist. I suppress the subscripts m and t in this section. The production of intermediate goods follows a linear technology:

$$y = l, \tag{5}$$

where l is the labor input. The wage rate of the labor is w.

Each intermediate goods producer also faces a regulatory burden τ in its production, which increases the marginal cost of production from w to $(1 + \tau)w$. The regulatory burden can include costs of compliance with relevant regulations, or costs of noncompliance such as penalties, litigation fees, and losses from operational disruptions.

I first consider an intermediate goods firm subject to this regulatory burden, and then discuss a firm that innovates to update its production process to reduce the regulatory burden. I solve the maximization problem of each firm and compare their optimal choices.

A. *Firms subject to regulations*

A monopolist that is subject to a regulatory burden maximizes profit as follows:

$$\pi^N = \max_l \{py - (1+\tau)wl\}, \quad \text{s.t.} \quad p = q^{\psi} y^{-\psi} \text{ and (5).} \tag{6}$$

The first order condition generates the firm's optimal choice of labor input: $l^N = \left[\frac{1-\psi}{(1+\tau)w}\right]^{\frac{1}{\psi}} q$. Accordingly, the firm's output is $y^N = l^N$, revenue is $R^N = \left[\frac{1-\psi}{(1+\tau)w}\right]^{\frac{1-\psi}{\psi}} q$, and profit is:

$$\pi^N = \tilde{\pi}(1+\tau)^{-\frac{1-\psi}{\psi}} q, \tag{7}$$

where $\tilde{\pi} \equiv \psi(\frac{1-\psi}{w})^{\frac{1-\psi}{\psi}}$.

B. *Firms with regulation-driven innovations*

A monopolist that is subject to the same regulatory burden can adopt a regulation-driven innovation, which updates its production process such that it can produce the intermediate goods with the same quality (q) at a lower regulatory cost. The idea is that the updated process either reduces the cost of regulatory compliance or circumvent regulatory requirements, thereby reducing regulatory burden. The firm pays a fixed cost of w_0 for adopting the regulation-driven innovation, which can be considered as the cost of R&D paid at the time of adoption or the cost of implementing the technology in production.

The reduction of regulatory burden depends on the extent to which the innovation (or the updated production process) is aligned with regulations. Specifically, the marginal cost of production becomes $[(1 + (1 - \xi)\tau]w$, where $\xi \sim F(0, 1]$ denotes the level of innovation-regulation alignment. I assume that the realization of ξ is exogenous and has the distribution of $F(\cdot)$. In an extreme case, when the regulation-driven innovation completely aligns with existing regulations (i.e., $\xi = 1$), the firm faces no regulatory burden.

The firm maximizes profit as follows:

$$\pi^R = \max_l \{py - \left[1 + (1-\xi)\tau\right] wl - w_0\}, \quad \text{s.t.} \quad p = q^{\psi} y^{-\psi} \text{ and (5).} \tag{8}$$

The firm's optimal choice of labor is $l^A = \left[\frac{1-\psi}{[1+(1-\xi)\tau]w}\right]^{\frac{1}{\psi}} q$; output is $y^A = l^A$; revenue is $R^A = \left[\frac{1-\psi}{[1+(1-\xi)\tau]w}\right]^{\frac{1-\psi}{\psi}} q$; and profit is

$$\pi^A = \tilde{\pi} \left[1 + (1-\xi)\tau\right]^{-\frac{1-\psi}{\psi}} q - w_0. \tag{9}$$

As shown in Table 1, comparing the optimal choices of the two types of firms, firms with regulation-driven innovations have higher labor input, output, and revenue than firms without such innovations. That is, for a firm producing intermediate goods with given quality q and facing a regulatory burden, adopting a regulation-driven innovation that updates its production process will results in growth in its employment, output, and revenue. In sum:

Proposition 1 *Regulation-driven innovations lead to firm growth in terms of employment, output, and revenue.*

Moreover, as ξ increases, labor input ($\frac{\partial l^A}{\partial \xi} > 0$), output($\frac{\partial y^A}{\partial \xi} > 0$), and revenue ($\frac{\partial R^A}{\partial \xi} > 0$) of the firm with regulation-driven innovations increase, so the magnitude of growth increases. Therefore, the model suggests that:

Proposition 2 *The growth of firms with regulation-driven innovations becomes larger as the level of innovation-regulation alignment increases.*

While the realization of innovation-regulation alignment is exogenous, whether to adopt the regulation-driven innovation is an endogenous decision for the firm. Firms will choose to do so if $\pi^A(q) > \pi^N(q)$. Using (7) and (9), we can derive the equilibrium threshold in the static environment, $\hat{q}^s$, such that firms will choose to adopt regulation-driven innovations if

Table 1: Optimal Choices for Firms With and Without Regulation-Driven Innovations

	Firm N	*Firm A*	*Comparison*	*Changes as* $\xi \uparrow$
Labor (l)	$\left[\frac{1-\beta}{(1+\tau)w}\right]^{\frac{1}{\beta}} q$	$\left[\frac{1-\beta}{[1+(1-\xi)\tau]w}\right]^{\frac{1}{\beta}} q$	$l^N < l^A$	$\lvert l^A - l^N \rvert \uparrow$
Output (y)	$\left[\frac{1-\beta}{(1+\tau)w}\right]^{\frac{1}{\beta}} q$	$\left[\frac{1-\beta}{[1+(1-\xi)\tau]w}\right]^{\frac{1}{\beta}} q$	$y^N < y^A$	$\lvert y^A - y^N \rvert \uparrow$
Revenue (R)	$\left[\frac{1-\beta}{(1+\tau)w}\right]^{\frac{1-\beta}{\beta}} q$	$\left[\frac{1-\beta}{[1+(1-\xi)\tau]w}\right]^{\frac{1-\beta}{\beta}} q$	$R^N < R^A$	$\lvert R^A - R^N \rvert \uparrow$

and only if:

$$q > \hat{q}^s \equiv \frac{w_0}{\tilde{\pi}\left(\left[1+(1-\xi)\tau\right]^{-\frac{1-\psi}{\psi}} - (1+\tau)^{-\frac{1-\psi}{\psi}}\right)}. \tag{10}$$

Therefore, only firms with sufficiently large quality chooses to update their production processes in response to regulations. Since labor, output, and revenue are all functions of q, it implies that larger firms are more incentivized to adopt regulation-driven innovations. The intuition is that the payoff from adopting such innovations becomes more appealing as the regulatory cost increases with firm size.

For the sake of simplicity, I assume $\psi = 0.5$ for the rest of the model discussion. Hence the static threshold becomes:

$$q > w_0 \left(\tilde{\pi}\left[\frac{1}{1+(1-\xi)\tau} - \frac{1}{1+\tau}\right]\right)^{-1}. \tag{11}$$

2.2 Dynamic Environment

In a dynamic environment, firms enter the market with new innovative ideas that improve product quality and can potentially replace incumbents. A potential entrant receives a new quality-improving innovative idea at Poisson arrival rate σ and produces a new vintage $M+1$, which improves the quality of the most recent vintage M by λ as follows:

$$q_{M+1} = (1+\lambda)q_M, \tag{12}$$

where $\lambda \sim G(0, \infty)$ denotes the realization of quality according to the distribution $G(\cdot)$. Note that quality-improving innovations are distinct from regulation-driven innovations, as the latter only update the production process with reduced regulatory burden but do not change the quality of goods.

As a prerequisite for adopting regulation-driven innovations in the production process, firms must first acquire sufficient knowledge about relevant regulatory requirements. This resembles real-world practices as regulated entities often consult with legal experts and seek guidance from regulators on how to comply with regulations. Firms start with one of two states ($s \in \{0, 1\}$) regarding this required regulatory information. I assume that a share α of entrants have the regulatory information (i.e., $s = 1$), and $1 - \alpha$ have no such information (i.e., $s = 0$). Firms switch from $s = 0$ to $s = 1$ at the Poisson arrival rate ζ.

An entrant will replace the incumbent if its quality-adjusted cost is lower. That is, the entrant must have a higher quality-to-price ratio to beat the incumbent in a pricing game:

$$\frac{q_{M+1}}{p_{M+1}} > \frac{q_M}{p_M}. \tag{13}$$

In a standard Schumpeterian model, entrants replace incumbents by making any quality improvement $\lambda > 0$, and the rate of creative destruction is σ (Aghion and Howitt, 1992). In an economy where the incumbent can adopt a regulation-driven innovation to reduce its regulatory burden, however, the entrant must possess much higher quality to beat the cost advantage of the incumbent. To see the specific conditions under which the entrant replaces the incumbent in this economy, we can consider four different cases.

In the first case, neither the incumbent nor the entrant has regulation-driven innovations adopted. In the price competition, the lowest price that both firms can charge is $(1 + \tau)w$. Substituting that into (13) yields $\lambda > 0$. Hence, any improvement in quality will be sufficient for the entrant to replace the incumbent. The condition is also satisfied in the second case, where the entrant has regulation-driven innovations adopted while the incumbent does not.

The entrant can charge a lower price $[1 + (1 - \xi)\tau]w$, so any quality improvement will be sufficient. In the third case, both the incumbent and the entrant have regulation-driven innovations adopted. Similar to the first case, neither firm has any cost advantage. The entrant will replace the incumbent by making any quality improvement $\lambda > 0$. In the first three cases, therefore, the model is similar to a standard Schumpeterian economy, in which entrants replace incumbents at the rate σ (Aghion and Howitt, 1992).

The fourth, and perhaps most interesting, case is that the incumbent has regulation-driven innovations adopted, but the entrant does not. This asymmetry leads to a regulatory advantage of the incumbent, and the entrant needs to have sufficiently higher quality to replace the incumbent. The lowest price that the incumbent can charge now is $[1+(1-\xi)\tau]w$, and the price for the entrant is $(1 + \tau)w$. The condition in (13) gives a quality threshold λ^* such that the entrant will replace the incumbent if and only if:

$$\lambda > \lambda^* \equiv \frac{\xi\tau}{1 + (1 - \xi)\tau}. \tag{14}$$

This also equals the regulatory advantage that the incumbent has as a result of regulation-driven innovations.

To see when the incumbent chooses to adopt regulation-driven innovations in the dynamic setting, I start by writing down the value function of the incumbent. I first assume that there is a dynamic quality threshold $\hat{q}^d$, such that firms with $q > \hat{q}^d$ choose to adopt regulation-driven innovations, and I ultimately solve the threshold $\hat{q}^d$.

Incumbents with $q < \hat{q}^d$. Consider an incumbent firm with quality lower than the threshold and denote its value function by V_{-1}. The firm can operate to get instantaneous profits π^N but will be replaced and exit the market at the rate σ, so we have the following:

$$rV_{-1}(q) = \underbrace{\tilde{\pi}(1 + \tau)^{-1}q}_{\pi^N} - \underbrace{\sigma V_{-1}(q)}_{\text{replaced}}, \tag{15}$$

where $r > 0$ is the exogenous risk-free interest rate. The left-hand side of this equation represents the safe return, and the right-hand side denotes the risky return. Rearranging equation (15) gives:

$$V_{-1}(q) = \frac{\tilde{\pi}(1+\tau)^{-1}}{r+\sigma} q. \tag{16}$$

Incumbents with $q \geq \hat{q}^d$ in state $s = 0$. Now the incumbent has quality above the threshold $q \geq \hat{q}^d$ but starts with no regulatory information required for regulation-driven innovations ($s = 0$), and its value function is V_0. Similarly, the firm can collect profits π^N and get replaced at the rate σ, but it will also acquire regulatory information ($s = 1$) at the rate ζ. Equating its safe return with risky return generates:

$$rV_0(q) = \underbrace{\tilde{\pi}(1+\tau)^{-1}q}_{\pi^N} - \underbrace{\sigma V_0(q)}_{\text{replaced}} + \underbrace{\zeta\left(V_1(q) - V_0(q)\right)}_{\text{get regulatory information}}, \tag{17}$$

where V_1 denotes the value function of a firm in state $s = 1$ with $q \geq \hat{q}^d$.

Incumbents with $q \geq \hat{q}^d$ in state $s = 1$. The incumbent with regulatory information ($s = 1$) and $q \geq \hat{q}^d$ can collect the profit π^A but is replaced at a different rate, depending on whether the entrant has regulatory information or not. Therefore, the firm has the following value function:

$$rV_1(q) = \underbrace{\tilde{\pi}\left[1+(1-\xi)\tau\right]^{-1}q - w_0}_{\pi^A} - \sigma\Big[\underbrace{\alpha}_{\substack{\text{with regulatory}\\ \text{information}}} + \underbrace{(1-\alpha)Pr(\lambda > \lambda^*)}_{\substack{\text{no regulatory information}\\ \text{but major quality improvement}}}\Big]V_1(q). \tag{18}$$

Rearranging (18) gives:

$$V_1(q) = \frac{\tilde{\pi}\left[1+(1-\xi)\tau\right]^{-1}q - w_0}{r+\tilde{\sigma}}, \tag{19}$$

where $\tilde{\sigma} \equiv \sigma\left[\alpha + (1-\alpha)Pr(\lambda > \lambda^*)\right]$.

The incumbent will adopt regulation-driven innovations if and only if such innovations bring more value to the firm: $V_1(q) > V_{-1}(q)$. Using (16) and (19), we can solve for the dynamic threshold $\hat{q}^d$:

$$q > \hat{q}^d \equiv w_0 \left(\tilde{\pi} \left[\frac{1}{1+(1-\xi)\tau} - \frac{r+\tilde{\sigma}}{r+\sigma} \frac{1}{1+\tau} \right] \right)^{-1}. \tag{20}$$

Comparing the static and dynamic thresholds yields:

$$\hat{q}^s = w_0 \left(\tilde{\pi} \left[\frac{1}{1+(1-\xi)\tau} - \frac{1}{1+\tau} \right] \right)^{-1} > w_0 \left(\tilde{\pi} \left[\frac{1}{1+(1-\xi)\tau} - \frac{r+\tilde{\sigma}}{r+\sigma} \frac{1}{1+\tau} \right] \right)^{-1} = \hat{q}^d, \tag{21}$$

given $\tilde{\sigma} = \sigma \left[\alpha + (1-\alpha) Pr(\lambda > \lambda^*) \right] < \sigma$. The gap between $\hat{q}^d$ and $\hat{q}^s$ means that:

Proposition 3 *In a dynamic environment, incumbent firms have an additional preemptive motive to adopt regulation-driven innovations.*

The additional preemptive motive results from the benefits that incumbents anticipate getting by discouraging entry and restricting competition if they adopt regulation-driven innovations. Consequently, these incumbents gain more market power and survive longer. Note that as ξ increases, $\lambda^* = \frac{\xi\tau}{1+(1-\xi)\tau}$ increases and thus $Pr(\lambda > \lambda^*)$ decreases, so $\tilde{\sigma}$ decreases ($\frac{\partial\tilde{\sigma}}{\partial\xi} < 0$). As a result, the gap between $\hat{q}^d$ and $\hat{q}^s$ further widens, so the incumbent faces even more additional preemptive motive to invest in regulation-driven innovations. This is intuitive as higher innovation-regulation alignment provides larger regulatory advantage to incumbents if they adopt regulation-driven innovations.

The equilibrium creative destruction rate is:

$$\text{Entry rate} = \begin{cases} \sigma & \text{if incumbents do not adopt regulation-driven innovations,} \\ \tilde{\sigma} & \text{if incumbents adopt regulation-driven innovations.} \end{cases}$$

With $\tilde{\sigma} < \sigma$, the model implies that:

Proposition 4 *Regulation-driven innovations slow down creative destruction.*

When incumbents have such innovations adopted, entrants face more barriers to entry, as they must achieve higher quality improvements to replace incumbents.

Also, as the level of innovation-regulation alignment ξ increases, the rate of creative destruction $\tilde{\sigma}$ further decreases ($\frac{\partial \tilde{\sigma}}{\partial \xi} < 0$). This leads to the following:

Proposition 5 *The rate of creative destruction further decreases as the level of innovation-regulation alignment increases.*

In the following sections, I examine these model implications empirically by identifying regulation-driven innovations from U.S. patents and constructing a text-based measure of innovation-regulation alignment.

3 Measuring Regulatory Alignment of Patents

I construct a measure of regulatory alignment for each U.S. patent granted between 1976 and 2020, based on textual similarity between patent documents and federal regulations. This section describes the data and methodology for constructing the measure as well as descriptive statistics.

3.1 Text Data

I obtain text data for estimating textual similarity between patents and regulations from two sources. The patent text data are from the PatentsView database, which complies the full text, abstract, and various metadata of U.S. patents beginning in 1976 from the U.S. Patent and Trademark Offic (USPTO). The original dataset includes 7,627,229 patents in total published from 1976 to 2020. As a common approach in the literature, I focus the analysis on utility patents, which include 6,913,035 patents.[1] My analysis of the patent text

[1]Utility patents are those "granted to anyone who invents or discovers a new and useful process, machine, article of manufacture, or composition of matter, or any new and useful improvements of these" (see https://www.uspto.gov/patents/basics/apply). In addition to utility patents, there are design patents and plant patents.

uses the abstract for each patent, so I further omit 796 patents without an abstract. As a result, the patent corpus for analysis covers 6,912,239 patents granted between 1976 and 2020.

The regulatory text comes from the Code of Federal Regulations (CFR). The CFR is the official annual edition containing the codification of the general and permanent rules issued by the U.S. federal government. The CFR represents the stock of federal regulations, meaning that the regulations that are active and being enforced will be published in each annual edition of the CFR. To capture the regulations in effect when a patent was filed and granted, I analyze the CFR parts published both within the five years preceding the patent's grant year and during the grant year itself. Therefore, the regulatory corpus includes the CFR published between 1971 and 2020. I obtain the CFR text data from ProQuest.

Since each volume of the CFR contains thousands of pages, I compare a patent's abstract with each "part" in the CFR and estimate their textual similarity. The CFR has a hierarchical structure and is divided into 50 titles that represent broad areas subject to federal regulation, such as agriculture, energy, banks and banking, food and drugs, and protection of environment. Each title is further divided into chapters, subchapters, parts, and sections, ranging from very broad to very granular content. A part typically points to a single program or function (Al-Ubaydli and McLaughlin, 2017), so it is appropriate to use part as the unit of analysis. The number of parts in the CFR increased over time, from approximately 4,500 parts in the 1971 edition to over 8,000 parts in 2020. In total, there are 358,367 CFR parts published between 1971 and 2020.

3.2 Methodology

To estimate the textual similarity between a patent abstract and a CFR part, the first task is to get numerical representations of the documents. The most common approach used to convert text to numbers in the literature is the bag-of-words approach (Gentzkow et al., 2019). A simple version of the bag-of-words approach entails counting how many times each unique word appears in a document. A more sophisticated variant of this approach is TF-IDF (term frequency-inverse document frequency), which takes into account how relevant a word is to a document in a collection of documents. TF-IDF provides an effective representation of text and has been used successfully in many prior studies analyzing textual similarity (Kelly et al., 2021; Biasi and Ma, 2022). For example, Kelly et al. (2021) use a modified version of the TF-IDF measure to estimate textual similarity between two patent documents, thereby measuring a patent's novelty and impact. However, the TF-IDF approach is not suitable for this study, because I compare two different sets of documents—patents and regulations. The vocabulary used in patents is likely to be different from that used in regulations, so a TF-IDF representation would underestimate the similarity (Kogan et al., 2021).

Instead, neural network-based embeddings are a type of text representations that capture the semantic meaning of text and have been widely used in many deep learning applications (Gentzkow et al., 2019). An embedding maps a piece of text into a high-dimensional latent space and expresses it as a dense vector. In the vector space, words with similar semantic meanings are closely positioned. A well-known example is $king - man + woman \approx queen$, that is, subtracting the vector *man* from the vector *king* and then adding it by *woman* will arrive a position close to *queen* (Gentzkow et al., 2019). One of those embedding techniques is the transformer architecture, which captures not only the semantic meaning but also the sequential nature of a text (Vaswani et al., 2017). The sequential order of words is important in natural language. For example, "kids eat apples" and "apples eat kids" should have completely different meanings. Since introduced, transfomers have become the core of the current generation of large language models and led to the development of pre-trained models such as BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018). Over the past few years, various other pre-trained models have been developed, extending and optimizing the original BERT model for specific NLP tasks.

To obtain embeddings of patent and CFR text, I use a pretained Sentence-BERT model. Sentence-BERT, or Sentence Transformers, provides a state-of-the-art framework for text and image embeddings (Reimers and Gurevych, 2019). This framework is particularly effective and efficient for semantic similarity comparison for sentences or short paragraphs. Embeddings of two pieces of text generated by Sentence-BERT can be compared using a similarity measure such as cosine similarity or Euclidean distance. Sentence-BERT provides various pretrained models, and the one used in this study is *all-mpnet-base-v2*, which was trained on a large dataset of over one billion training pairs and evaluated to have the best average performance compared to other general-purpose pretrained models.[2] The model maps sentences and paragraphs to a 768 dimensional dense vector space.

To illustrate the idea of the textual similarity analysis, the following shows three sequences of text and how they compare with each other using Sentence-BERT:[3]

Sequence 1: A regulation is a set of requirements issued by a federal government agency to implement laws passed by Congress.

Embedding 1: $[0.026, -0.057, 0.001, ..., 0.029, -0.010, 0.013]_{1\times768}$

Sequence 2: A regulation is a general statement issued by an agency, board, or commission that has the force and effect of law.

Embedding 2: $[0.035, -0.074, 0.015, ..., 0.038, -0.007, 0.007]_{1\times768}$

Sequence 3: Natural language processing (NLP) is a machine learning technology that gives computers the ability to interpret, manipulate, and comprehend human language.

Embedding 3: $[0.044, 0.013, -0.015, ..., 0.002, -0.005, 0.007]_{1\times768}$

Textual similarity scores:

	1	**2**	**3**
1	1.000		
2	0.872	1.000	
3	0.107	0.123	1.000

[2]See `https://www.sbert.net/docs/pretrained_models.html` and `https://huggingface.co/sentence-transformers/all-mpnet-base-v2`.

[3]These sequences are text from the web for illustrative purposes only. Sequence 1 is from the Federal Reserve Board website (`https://www.federalreserve.gov/faqs/what-is-a-regulation.htm`); sequence 2 is from reginfo.gov (`https://www.reginfo.gov/public/jsp/Utilities/faq.myjsp#reg_rule`); and sequence 3 is from the Amazon Web Services website (`https://aws.amazon.com/what-is/nlp/`).

Since the embeddings generated by Sentence-BERT can contain negative values, the textual similarity score lies in the interval of [-1,1]. Two identical sequences would generate a textual similarity score of 1.

A challenge in estimating textual similarity using Sentence-BERT in this study is that CFR parts vary substantially in length, ranging from dozens to several millions of words.[4] Like other BERT-based models, the sentence-transformer model *all-mpnet-base-v2* has a sequence limit such that input text longer than 384 word pieces is truncated. To ensure that no important information from the CFR is missed due to text truncation while also maintaining reasonable computing time, I split each CFR part into smaller chunks, with each chunk containing up to 3,000 words.[5] I then compute the cosine similarity between the patent abstract and each chunk of the CFR part and take the maximum similarity as the similarity between the patent and the CFR part. Formally, the textual similarity score between a patent i and a CFR part j, $\rho_{i,j}$, is:

$$\rho_{i,j} = \max_{q \in \Omega_j} \{ \frac{V_i}{\|V_i\|} \cdot \frac{V_q}{\|V_q\|} \}, \tag{22}$$

where Ω_j denotes the set of text chunks of CFR part j, V_i denotes the embedding vector for the abstract of patent i, and V_q is the embedding vector for CFR text chunk $q \in \Omega_j$. The patent-CFR pair with highly similar semantic meanings will have a high similarity score ρ.

As such, I estimate textual similarities for each patent with all the CFR parts published

[4] The average length of the CFR parts in the data is 8,180 words, and the median is 2,776. Approximately 56 percent of the CFR parts have a length between 1,000 and 10,000 words. Some CFR parts are particularly long, such as Title 26 Part 1, which codifies the Internal Revenue Service's regulations on income taxes and has over five million words.

[5] I determine the chunk size of 3,000 words to balance accuracy and computational efficiency. Theoretically, splitting a long text into chunks with less than 384 word pieces would ensure absolutely no information loss during text truncation. However, there are at least two drawbacks in that approach. First, analyzing individual small text chunks separately may lose the context in which a text chunk is discussed and not capture its semantic meaning correctly. Second, given the large number of patents and CFR parts, splitting each CFR part into a number of small chunks would significantly increase computational resource demands for estimating pairwise similarities, while the marginal improvement in performance may be minimal. Using the chunk size of 3,000 words, approximately 90 percent of the CFR parts are split into no more than five chunks, ensuring reasonable computing time.

within five years before and during the patent's grant year.[6] I then construct the measure of regulatory alignment for the patent by summing the similarity scores. Specifically, regulatory alignment of patent i is defined as:

$$R_i = \sum_{j \in \Theta_{j,T}} \mathbb{I}_i^{\lambda}(j) \times \rho_{i,j}, \tag{23}$$

where $\Theta_{i,T}$ denotes the set of CFR parts published during the grant year of patent i and within the preceding T years (in this case, $T = 5$), and $\mathbb{I}_i^{\lambda}(j)$ is an indicator function that equals 1 if CFR part j has a similarity score larger than or equal to a threshold λ with patent i (i.e., $\rho_{i,j} \geq \lambda$). As such, a patent with a positive regulatory alignment value ($R_i > 0$) means that the patent is highly similar to at least some regulatory text, and those patents are defined as *regulation-driven innovations* in this study.

Using the sum as an aggregating method, rather than alternatives like the mean or maximum, reflects the notion of cumulative regulatory burden.[7] Prior studies have shown that the cost of regulation is positively associated with the quantity of regulation (Coffey et al., 2020; Dawson and Seater, 2013; Mulligan and Shleifer, 2005). Consequently, a high alignment with 100 CFR parts should not be considered equivalent to alignment with just one part. Therefore, I posit that a patent with high similarities with a greater number of CFR parts is more closely aligned with federal regulations and could potentially mitigate a larger portion of the regulatory burden faced by the innovating firm.

Imposing a threshold restriction in equation (23) ensures that only sufficiently high similarity scores receive any weight in the construction of the measure. Since textual similarity tasks generally return continuous similarity or distance scores, it is almost always necessary

[6]As shown in Appendix C.2.1, the average time between the application date and the grant date of a patent in the data is 2.7 years. Covering the CFR published within five years before and during the patent's grant year ensures that the regulatory alignment measure captures the regulatory information available to the innovating firm when its patent was filed and granted.

[7]However, it is possible that the maximum similarity sometimes reflects the true alignment better than the sum. In that sense, my measure using the sum is a noisy measure of the true alignment. All else equal, this biases my estimates toward zero.

to derive a definition for when two documents are similar and when they are not (Cadamuro and Gruppo, 2023). Although it is impossible to know a clear cutoff without a large training dataset, I expect that only a small fraction of patents were driven by regulation, and thus the threshold λ needs to be sufficiently large to rule out false positives. Using a low λ may introduce noise into the measure and thus dilute any patterns the measure captures. As indicated by the three-sequence example above, a highly dissimilar pair could have a textual similarity score over 0.1. In fact, the majority of the patent-CFR pairwise similarities fall into the range of 0 to 0.3, as discussed in Section 3.3, meaning that most patents tend to be unrelated to regulation. The same pattern was also found in other studies examining textual similarities, such as Kelly et al. (2021) in estimating similarities across patents and Kogan et al. (2021) in comparing patents and occupation descriptions. Kogan et al. (2021) focus their analysis on patent-occupation pairs that are above the 80th percentile in textual similarity, while setting all other lower values to zero.

After selecting a random sample of patents and verifying the corresponding CFR parts at various similarity scores, I use $\lambda = 0.6$ as my baseline threshold. This threshold effectively excludes nearly all irrelevant regulations for a given patent. However, I acknowledge that this may not be the best threshold that distinguishes similar patent-CFR pairs from dissimilar ones. A lower threshold could capture a broader set of regulation-driven innovations, albeit with the risk of introducing too much noise into subsequent patent, firm, and macro-level analyses. A higher threshold might be more accurate in eliminating more false positives and generate stronger results in the empirical analyses. Therefore, I also use different threshold values in robustness checks.

3.3 Descriptive Statistics

Among all the applicable patent-CFR pairs, the most similar pair generates a textual similarity score $\rho = 0.89$. The minimum is -0.25, and the mean is 0.16. Given that there are on average 7,100 parts in an annual edition of the CFR, each of the 6,912,239 patents in the sample is paired with approximately 42,600 ($7,100 \times 6$ years) CFR parts. That results in roughly 320 billion patent-CFR pairs. This tremendously large number of pairs makes it computationally difficult to examine the full distribution of all pairwise similarity scores. However, it is possible to examine the distribution over smaller samples.

Examining the pairwise similarity distributions over smaller samples reveals that most scores fall into a positive range, and thus the threshold $\lambda = 0.6$ used in equation (23) only captures patent-CFR pairs in the right tail. These pairs represent cases where the patents are more likely to be regulation-driven innovations. Specifically, I select three samples to assess the extent to which a patent is typically "similar" to a CFR part. The first sample contains the maximum pairwise similarity score for each of the 6,912,239 patents, so each patent is associated with only one similarity score in this sample. The distribution therefore represents an "upper bound" of the distribution of all pairwise similarities. As shown in Appendix A.1, all the patents have positive textual similarities with at least one CFR part. Around 39 percent of the patents have similarities larger than 0.5 with at least one CFR part, and eight percent have similarities larger than 0.6. In the second sample, I select a random sample of 1,000 patents and examine their similarities with all the applicable CFR parts (Appendix A.2). The similarity scores fall into a range of smaller values, mostly from 0 to 0.4, since the random sample contains only a few (if any) regulation-driven innovations. The third sample contains 15 randomly selected patents and is intended to show the within-patent distribution of all pairwise similarities for each patent (Appendix A.3). Similarly, most scores range from 0 to 0.3.

Aggregating the pairwise similarities using equation (23) leads to eight percent of the patents (559,520 out of 6,912,239) with a positive regulatory alignment value ($R > 0$), meaning that these patents each have at least one highly similar CFR part. There is a large variation in regulatory alignment values among these patents, ranging from 0.6 to 861. The average regulatory alignment value is 6.5, the median is 3.6, and the standard deviation is 12.4. The distribution is right-skewed, with nearly 85 percent of the patents having a regulatory alignment value of 10 or less. That is, most regulation-driven innovations are only associated with a few highly similar CFR parts. That is intuitive, as it is less likely that a single patent can align with a large number of regulations. The next section discusses specific examples of patent-CFR pairs.

4 Validation and Interpretation

To verify that the measure correctly captures the extent to which a patent is aligned with regulations, I examine specific examples of patents and their most similar CFR parts. Some patents contain explicit references to specific regulatory requirements, leading to a high textual similarity score with the referenced regulations. Those with relatively low similarity scores represent innovations that are more implicitly subject to a set of existing regulations. I also discuss some descriptive patterns in the resulting regulatory alignment measure.

4.1 Illustrative Examples

Table 2 lists illustrative examples of patent-CFR pairs with various similarity scores above 0.6. Patents with extremely high similarity to CFR parts tend to explicitly reference related regulations. For example, Patent 8,750,290 "Method and apparatus for ensuring accessibility to emergency service via VoIP or via PSTN" presents an invention developed to guarantee compliance with the Federal Communications Commission (FCC)'s Order 05-116 that requires interconnected Voice over Internet Protocol (VoIP) service providers to deliver all emergency service calls to a VoIP service user's local emergency service operator. The most similar CFR part to this patent is Title 47 Part 9 "Interconnected Voice Over Internet Protocol Services," which codifies the FCC order.

The patent "D-ring height adjuster" (5,794,977) describes an invention of a seat belt webbing height adjuster, which is a vehicle occupant safety apparatus. Federal law has required all vehicles to be equipped with seat belts since 1960s, and specific requirements

Table 2: Illustrative Examples of Similar Patent-CFR Pairs

	Patent (i)	CFR Part (j)	$\rho_{i,j}$
(1)	Method and apparatus for ensuring accessibility to emergency service via VoIP or via PSTN (8,750,290)	Interconnected Voice Over Internet Protocol Services (47 CFR 9)	0.81
(2)	D-ring height adjuster (5,794,977)	Federal Motor Vehicle Safety Standards (49 CFR 571)	0.80
(3)	Combustion control for producing low NOx emissions through use of flame spectroscopy (5,480,298)	Acid Rain Nitrogen Oxides Emission Reduction Program (40 CFR 76)	0.75
(4)	Promoting compliance by financial institutions with due diligence requirements (7,930,228)	Financial Recordkeeping And Reporting of Currency And Foreign Transactions (31 CFR 103)	0.75
(5)	Radio telecommunication network with selectable ring signal coverage (5,809,396)	Frequency Allocations and Radio Treaty Matters; General Rules and Regulations (47 CFR 2)	0.70
(6)	Implantable system for glucose monitoring using fluorescence quenching (7,704,704)	Immunology and Microbiology Devices (21 CFR 866)	0.69
(7)	Systems and methods for providing a customer service (10,453,087)	Truth in Lending (Regulation Z) (12 CFR 226)	0.67
(8)	Gaming method and apparatus utilizing secondary software applications (8,187,103)	Minimum Technical Standards for Gaming Equipment Used with the Play of Class II Games (25 CFR 547)	0.61

are prescribed in CFR Title 49 Part 571 "Federal Motor Vehicle Safety Standards." The textual analysis indicates that this patent-CFR pair has a high similarity of 0.8.

Patent 5,480,298 is an example of innovations driven by environmental regulation. It contains an invention for reducing nitrogen oxides (NOx) emissions from boiler burner combustion. NOx are air pollutants that contribute to the formation of acid rain and have been regulated at the federal level. CFR Title 40 Part 76 specifies emission limitations for NOx, particularly from coal-fired utility units.

The patent titled "Promoting compliance by financial institutions with due diligence requirements" (7,930,228) contains technologies "relate[d] to collecting, analyzing, storing and processing data and information in connection with compliance with regulatory and/or statutory legal requirements." In particular, the patent document describes the need for financial institutions to comply with due diligence requirements imposed on accounts of certain foreign financial institutions to address money laundering risks. CFR Title 31 Part 103 "Financial Recordkeeping And Reporting of Currency And Foreign Transactions" is identified as the most similar CFR part to the patent, which specifies anti-money laundering program requirements.

The other examples also suggest plausible connections between patents and regulations. Patent 7,704,704 relates to systems, devices, and methods of sensing an analyte that can be applied to glucose sensing, which is subject to the Food and Drug Administration's regulations on immunology and microbiology devices (21 CFR 866). The patent on "systems and methods for providing a customer service" (10,453,087) includes systems and methods for providing customer service such as secondary benefits of credit cards. Such application is closely related to Regulation Z issued by the Federal Reserve Board that governs the credit and lending industry.

These examples illustrate that the NLP method used correctly identify patents related to federal regulations. The estimated textual similarity scores depend on the extent to which the patent document explicitly references related regulatory requirements or compliance.

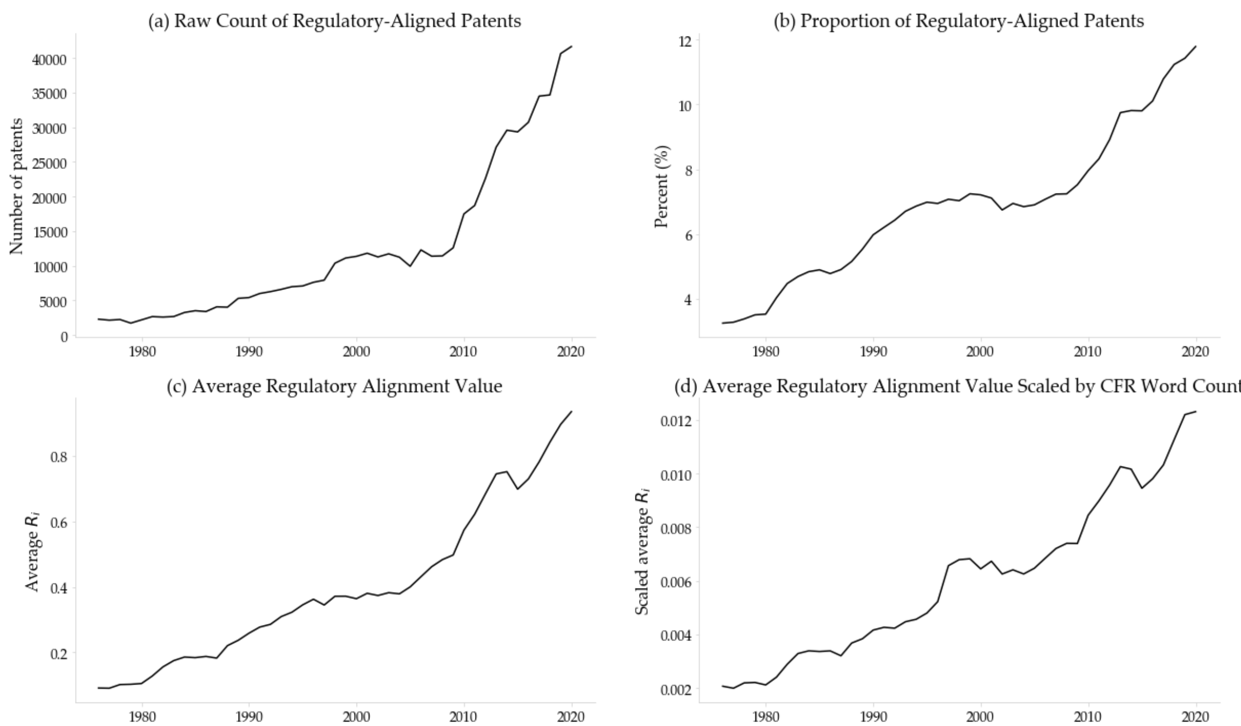
4.2 Descriptive Patterns in Regulatory Alignment

Aggregating pairwise similarities to the regulatory alignment measure allows us to observe patent-level patterns, both over time and across technology classes and regulatory areas.

Trends Over Time

Figure 1 shows changes in patent-level regulatory alignment by year over the period 1976-2020. As shown in Panels (a) and (b), both the raw count and proportion of regulatory-aligned patents increased over time. Also, the annual average of regulatory alignment value exhibits a similar increasing trend (Panel (c)). Given that the regulatory alignment measure represents a sum of highly similar CFR parts, this trend could be driven by the increasing volume of federal regulations (Al-Ubaydli and McLaughlin, 2017). I therefore further scale the annual average regulatory alignment values by CFR word counts. Panel (d) indicates that, controlling for the volume of regulations, the extent to which patents are aligned with existing regulations has still been increasing over time. While not the focus of this paper, these trends imply that firms may have become more aware of the private value in exploiting regulation through their innovation activities and are increasingly using it as a tool to maintain their market positions.

Figure 1: Regulatory Alignment of Patents Over Time



Notes: Panel (a) plots the count of regulatory-aligned patents (i.e., patents with positive regulatory alignment values ($R_i > 0$) in a given year. Panel (b) plots the proportion of regulatory-aligned patents in all patents granted in a given year. Panel (c) plots the annual average of regulatory alignment values (R_i) over all patents granted in a given year. Panel (d) plots the annual average of regulatory alignment values in a given year scaled by the total word count of the CFR published in that year.

Technology Classes

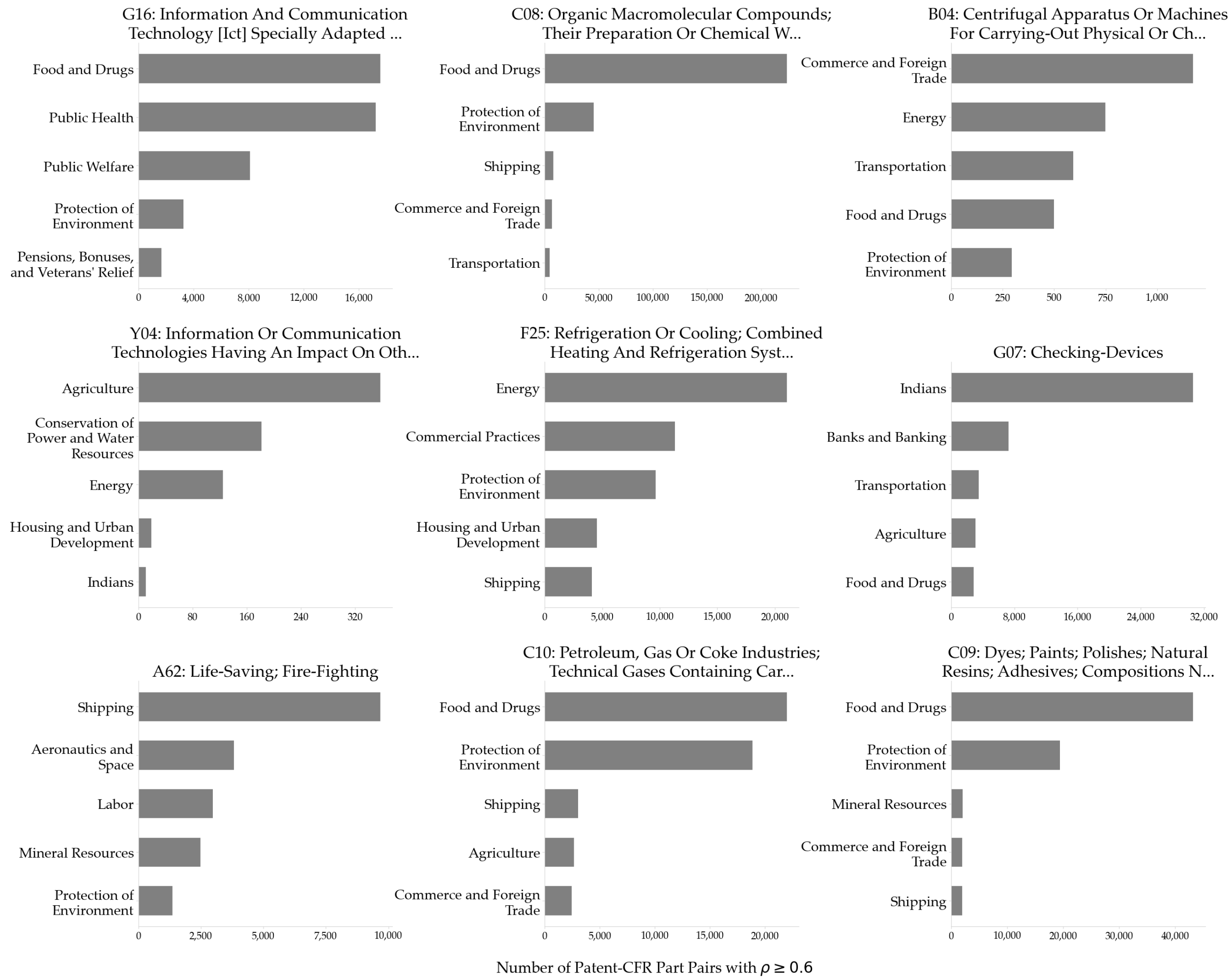
Using the Cooperative Patent Classification (CPC) of patents, I examine regulatory alignment across patents' technology classes.[8] As shown in Appendix B.1, the ICT class (G16) is the leading technology class, both in terms of the share of patents with positive regulatory alignment values and the average regulatory alignment value across patents. Approximately 31 percent of the patents in this class have a positive regulatory alignment value, and the average value is 3.68. ICT technologies have modernized business operations in various areas, and this analysis shows that they have also served as an effective tool for firms to respond to the regulations they are subject to.

Other technology classes with high proportions of regulatory-aligned patents include several chemistry-related classes (C08, C09, C10, and B04), refrigeration and heating systems (F25), life-saving and fire-fighting devices (A62), and agriculture (A01). Innovations in these technology classes can be driven by various regulations. For example, the technology classes related to the production and handling of chemicals (C08, B04, and C09) are likely subject to public health and workplace safety regulations; the fossil fuel (C10) and agriculture (A01) classes are associated with environmental regulations; and refrigeration, cooling, and heating systems (F25) are subject to energy efficiency standards.

I further verify these linkages by examining the most common CFR titles that the regulatory-aligned patents within each CPC class are similar to. As shown in Figure 2, regulatory-aligned patents in the ICT technology class are driven by regulations on food and drugs, public health, and public welfare. A large number of patents related to refrigeration, cooling, and heating systems are linked to energy and commercial practices regulations, as these appliances and equipment have been governed by established energy efficiency standards in the U.S. since 1975. Regulatory-aligned patents from petroleum, gas or coke indus-

[8]The CPC scheme has a hierarchical structure, consisted of section, class, subclass, group, and subgroup. A patent can be classified into multiple CPC groups that belong to multiple classes. My analysis is based on the most common CPC class of a patent. For a full list of the CPC scheme, see `https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html`.

Figure 2: CFR Titles Linked with Each CPC Class of Patents



Notes: The figure plots the five most common CFR titles that the regulatory-aligned patents within each CPC class are similar to.

tries are primarily associated with food and drugs and environmental regulations. Section 6 discusses more firm- and industry-level patterns.

Regulatory Areas

From a different angle, the linkages between CPC classes and CFR titles also allow us to investigate which regulatory areas have spurred the most regulation-driven innovations and what technology classes these innovations fall into. Intuitively, areas with more regulations should see a larger number of regulatory-aligned patents. Figure 3 presents the CFR titles with the largest numbers of similar patents. Food and drugs (Title 21), protection of environment (Title 40), and telecommunication (Title 47) are the top three areas. Most of the regulatory-aligned patents associated with food and drugs and environmental regulations are technologies for producing and handling chemicals and organisms, such as medical and veterinary equipment and processes, organic macromolecular compounds, organic chemistry, and related measuring and testing procedures. Electric communication techniques are a dominant class of innovations developed in response to telecommunication regulations, and transportation regulations (Title 49) have spurred vehicle-related innovations. As shown in Figures 2 and 3, the linkages between CPC classes and CFR titles are consistent with expectations, providing additional external validity for the regulatory alignment measure.

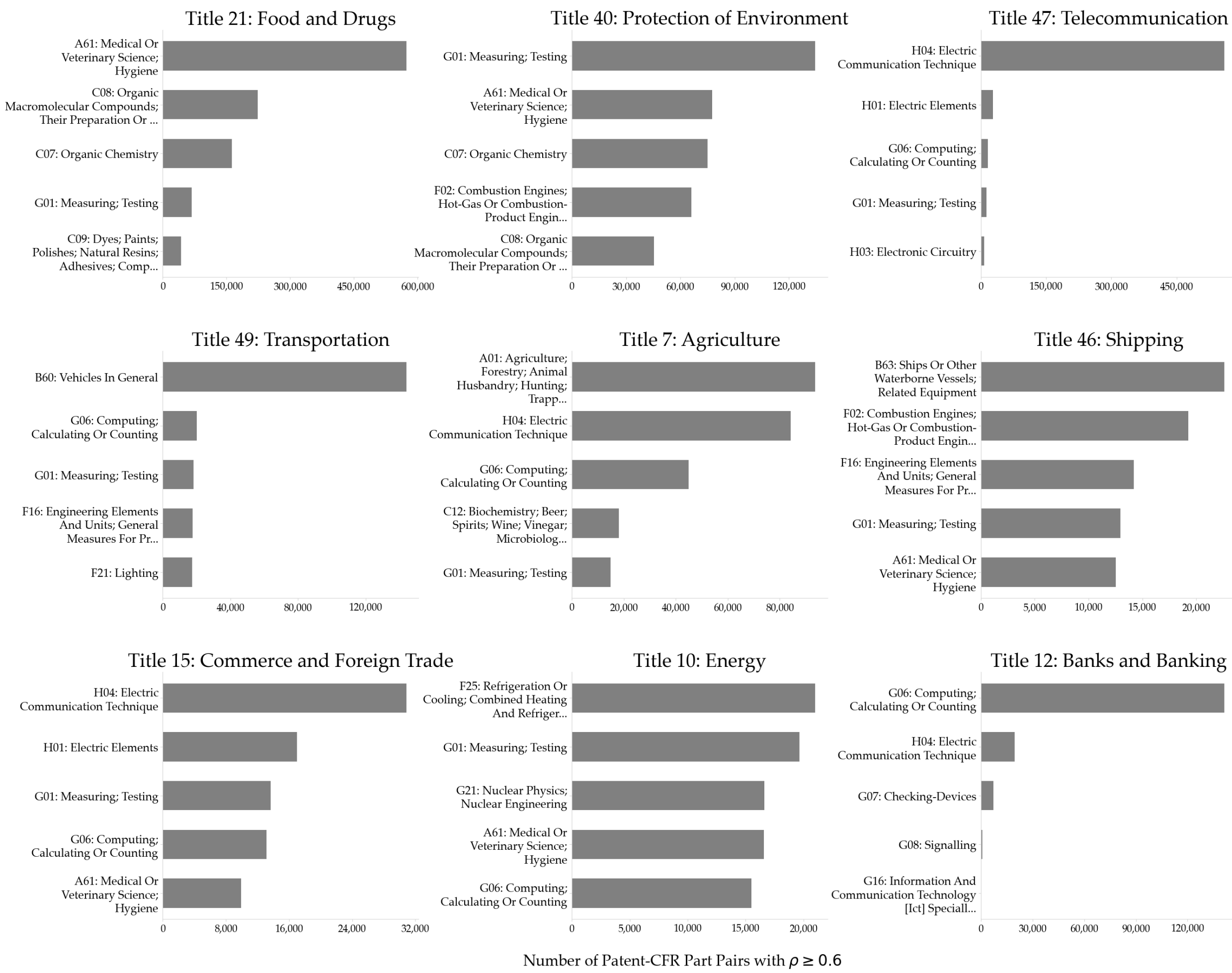
5 Regulatory Alignment and Patent Value

Before investigating the potential effects of regulation-driven innovations on firm dynamics and aggregate economic outcomes, I first evaluate the value of a regulation-driven innovation at the patent level. I examine the relation between a patent's regulatory alignment and its scientific and economic value.

5.1 Scientific Value

In the model described in Section 2, regulation-driven innovations are different from the innovations that improve the quality of a good. Although in the real world, there may be no clear line separating the two, we can evaluate whether regulation-driven innovations are associated with higher scientific value. The scientific value of patents has been studied extensively and commonly measured by forward citations—the number of times that a patent is cited in future patents (Lerner and Seru, 2022). However, patents continue to receive citations over long periods (which could be up to 50 years), and we only observe citations up

Figure 3: CPC Classes Linked with Each CFR Title



Notes: The figure plots the five most common CPC classes of the patents that are similar to regulations within each CFR title.

to the latest date of the available data (Hall and Trajtenberg, 2005).[9] Due to this truncation bias, raw counts of forward citations are not comparable with each other. For example, 10 citations received by a patent granted 20 years ago are not equivalent to 10 citations received by a patent granted five years ago. I address this issue by scaling a patent's raw count of forward citations by the average number of forward citations received by all the patents granted in the same year. Specifically, the measure of forward citations, $\tilde{C}$, is constructed

[9]When I collected the data, the citation data from PatentsView were updated through June 2022. Therefore, the raw count of citations is the total number of citations that a patent had received as of June 2022.

by:

$$\tilde{C}_i = \frac{C_i}{\frac{1}{N}\sum_{i' \in \mathcal{P}_i} C_{i'}}, \tag{24}$$

where C_i is the total number of forward citations received by patent i, $\mathcal{P}_i$ is the set of patents that were granted in the same year as patent i, and N is the number of patents in $\mathcal{P}_i$.[10]

I use the following empirical specification to examine the relation between regulatory alignment and forward citations:

$$asinh(\tilde{C}_i) = \alpha + \beta asinh(R_i) + \gamma Z_i + \varepsilon_i, \tag{25}$$

where Z includes a vector of control variables that may influence a patent's forward citations as identified in the literature, including backward citations, backward citation age, originality, grant lag, patent scope, number of claims, independent claims, dependent claim ratio, first claim length, shortest independent claim length, technology class (CPC) fixed effects, and grant year fixed effects or time trend. Since the forward citations and regulatory alignment variables contain many zero values, I take inverse hyperbolic sine (in lieu of natural logarithm) of both variables in the regression (Chen and Roth, 2024; Bellemare and Wichman, 2020). All the control variables are in logs except for originality, which ranges from 0 to 1. Appendix C.1 includes detailed descriptions of the control variables.

The citation and other patent-level data come from the PatentsView database. Of the 6,912,239 patents with regulatory alignment estimates, I exclude the patents with no CPC information, resulting in 6,900,262 patents used in this analysis. A substantial fraction of the patents (27 percent, or 1,829,065 patents) did not receive any citations. Appendix C.2.1 shows the descriptive statistics for all variables.

As shown in Table 3, the regression results suggest no statistically significant relationship between scientific value and regulatory alignment of patents. The results are robust when controlling for patent-level characteristics and replacing the year fixed effects with a time

[10] For robustness checks, I also use forward citations that a patent receives within 5 or 10 years after it is granted in lieu of truncation-adjusted forward citations in the regressions. The results are unchanged.

trend variable (see full results in Appendix C.3.1). To compare with the results on economic value of patents in the next section, I also restrict the data to patents assigned to publicly traded firms only. As shown in Appendix C.3.2, the results are similar to the baseline using all patents. These results indicate that regulation-driven innovations are likely to contribute little to technological advancement, confirming the distinction between regulation-driven innovations and quality-improving innovations in the model.

Table 3: Forward Citations and Regulatory Alignment of Patents

	(1)	**(2)**	**(3)**
Regulatory Alignment	0.002	-0.002	-0.004
	(0.004)	(0.004)	(0.005)
Patent Controls	NO	YES	YES
Technology Class FE	YES	YES	YES
Year FE	YES	YES	NO
Time Trend	NO	NO	YES
N	6,900,262	5,649,030	5,649,030
R^2	0.148	0.206	0.201

Notes: This table shows the estimated coefficients in equation (25). Full estimation results are available in Appendix C.3.1. Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

5.2 Economic Value

Kogan et al. (2017) argue that the private, economic value of innovations can be different from their scientific value, because an innovation "may represent only a minor scientific advance, yet be very effective in restricting competition, and thus generate large private rents" (Kogan et al., 2017, p.666). They therefore introduce a measure of the economic value of patents based on stock market reactions to patent grants (Kogan et al., 2017). Specifically, they estimate the economic value of a patent by exploiting the innovating firm's stock price movements within a narrow window around the patent issuance, adjusted for the component of the firm's stock return that is unrelated to the patent (Kogan et al., 2017). The estimated economic value is defined as "the present value of the monopoly rents associated with that patent" (Kogan et al., 2017, p. 671).

The model discussed in Section 2 predicts that regulation-driven innovations help the innovating firm deter competitors and thus bring them additional monopoly rents. Based on that, I expect to see a positive relationship between a patent's regulatory alignment and its economic value measured by Kogan et al. (2017). I estimate this relationship using the following empirical specification:

$$asinh(E_i) = \alpha + \beta asinh(R_i) + \gamma asinh(\tilde{C_i}) + \delta X_i + \mu_i, \tag{26}$$

where E_i is the economic value of patent i as measured by Kogan et al. (2017), and X is a vector of controls that includes the assignee firm's log total assets as a proxy of firm size, grant year fixed effects, and technology (CPC) class-specific grant year fixed effects or firm fixed effects.

Since the economic value measure is based on stock returns, the data are only available for patents assigned to publicly available firms. Upon merging the patent sample in this study with Kogan et al. (2017)'s dataset (updated through 2022), there are 2,368,490 matched patents (34 percent). The distribution of regulatory alignment values is similar to the full sample, with 192,754 patents (eight percent) associated with positive values, a mean of 6.6, and a median of 3.6. As Kogan et al. (2017)'s dataset also provides patent-CRSP firm match data, I further merge the patent data with the CRSP/Compustat database to obtain data on assignee firms' total assets (Compustat: AT), deflated by the Consumer Price Index (CPI) from the Bureau of Labor Statistics.[11] Appendix C.2.2 shows the descriptive statistics of the data used for this analysis.

Table 4 summarizes the estimation results. There is a strong and positive relationship between regulatory alignment and economic value of patents. Specifically, a one percent increase in a patent's regulatory alignment is associated with a 0.01-0.12 percent increase in

[11]Kogan et al. (2017) matched patents' assignee names with corporations in the CRSP/Compustat merged database. Part of the matching is from the NBER patent project (`https://sites.google.com/site/patentdataproject/`), and the remaining was conducted using a name matching algorithm developed by Kogan et al. (2017). Their updated dataset is available at `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`.

Table 4: Economic Value and Regulatory Alignment of Patents

	(1)	**(2)**	**(3)**	**(4)**
Regulatory Alignment	0.118***	0.112***	0.051***	0.012***
	(0.008)	(0.008)	(0.005)	(0.002)
Forward Citations		0.349***	0.308***	0.053***
		(0.014)	(0.010)	(0.005)
Firm Size		0.119***	0.141***	0.400***
		(0.009)	(0.009)	(0.03)
Year FE	YES	YES	YES	YES
Class×Year FE	NO	NO	YES	NO
Firm FE	NO	NO	NO	YES
N	2,368,490	2,315,437	2,312,677	2,315,437
R^2	0.030	0.069	0.175	0.810

Notes: This table shows the estimated coefficients in equation (26). Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

its economic value, depending on the controls used. Alternatively, for a patent with a median regulatory alignment value, being aligned with one additional CFR part (assuming $\rho = 0.6$) is associated with a 0.2-2.0 percent increase in the economic value of that patent.[12] The coefficients on forward citations are also statistically significantly positive, a result consistent with the finding of Kogan et al. (2017). The size of a patent's assignee firm is also positively associated with the patent's economic value, as larger firms may have more capacity to monetize the value of the patent. Taken together, these results suggest that regulation-driven innovations tend to achieve minimal scientific advance but generate tangible private rents. Next I further examine the relationship between regulation-driven innovations and firms' private gains using firm-level data.

6 Innovation-Regulation Alignment and Firm Outcomes

To further understand how the innovation activity driven by regulation might influence business dynamism, I aggregate the patent-level regulatory alignment measure into a firm-level

[12] As mentioned in Section 3.3, the median regulatory alignment value for the patents with positive values is 3.6. For a patent with the median value, as ρ increases by 0.6, its regulatory alignment value R increases by 0.6, which is approximately 17 percent increase in its regulatory alignment.

measure of innovation-regulation alignment. In this section, I describe the approach to aggregating the measure and present empirical evidence on its contributions to firm outcomes.

6.1 Firm-Level Innovation-Regulation Alignment

Following the approach in Kogan et al. (2017) to aggregating their economic value measure, I measure firm-level innovation-regulation alignment by summing up all the regulatory alignment values of patents that were granted to the firm in a year:

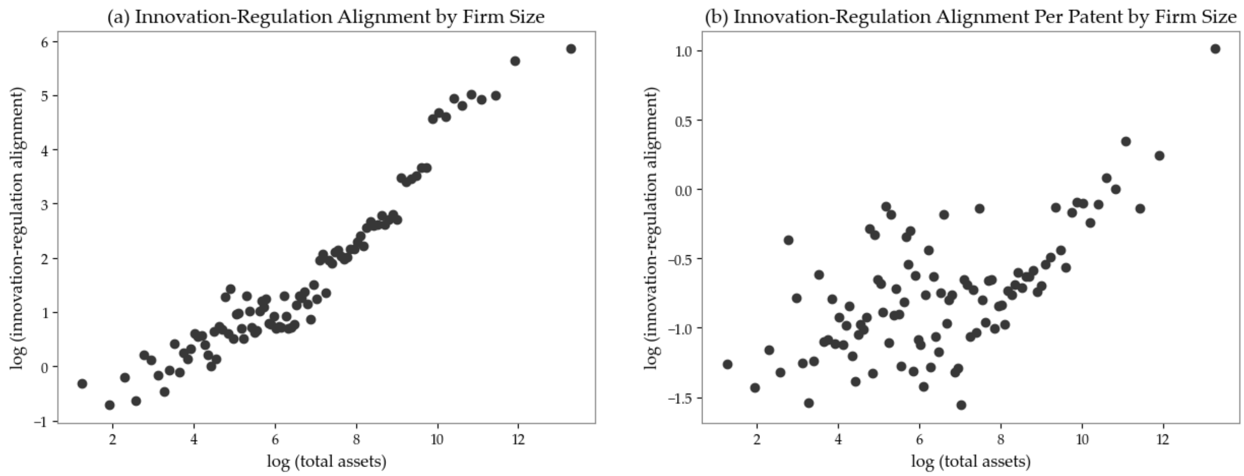
$$\xi_{f,t} = \sum_{i \in P_{f,t}} R_i, \tag{27}$$

where $\xi_{f,t}$ is firm f's innovation-regulation alignment in year t, and $P_{f,t}$ is the set of patents issued to firm f in year t.

As mentioned in Section 5.2, the patent-firm crosswalk from Kogan et al. (2017) matches 2,368,490 patents in the sample of this study. Those patents were assigned to 7,640 firms, covering 59,237 firm-year observations over the period of 1976-2020. Figure 4 divides firms' annual total assets into 100 quantiles and plots the log of the average innovation-regulation alignment ($\xi_{f,t}$) in each quantile. As shown in Panel (a), innovation-regulation alignment is monotonically increasing in firm size. A possible factor driving this pattern is that larger firms tend to file more patents. Therefore, I divide a firm's innovation-regulation alignment in a given year by the number of patents assigned to the firm in that year. Panel (b) plots the average innovation-regulation alignment per patent over the 100 quantiles of total assets. Controlling for patent counts, innovation-regulation alignment is still positively correlated with firm size. This observation is consistent with the model implication suggesting that larger firms optimally choose to adopt regulatory-aligned innovations to reduce regulatory burden.

Appendix D shows the industries (SIC-4) with the highest average per-patent innovation-regulation alignment and the leading firms within each industry. Industries with feder-

Figure 4: Innovation-Regulation Alignment and Firm Size



Notes: The figure plots the relation between firm size and firm innovation-regulation alignment. I group the firm-year innovation-regulation alignment data into 100 quantiles based on firms' total assets. In Panel (a), the horizontal axis plots the log of the average total assets in each quantile, and the vertical axis plots the log of the average innovation-regulation alignment ($\xi_{f,t}$) in each quantile. In Panel (b), the horizontal axis plots the log of the average total assets in each quantile, and the vertical axis plots the log of the average innovation-regulation alignment per patent in each quantile.

ally sponsored or federally chartered firms, such as Freddie Mac and Fannie Mae, tend to hold patents most closely aligned with federal regulations. Additionally, several medical and finance-related industries are also among those with the highest levels of innovation-regulation alignment.

6.2 Firm Growth and Market Power

Propositions 1 and 2 indicate that adopting a regulation-driven innovation in the production process leads to firm growth, and the growth is larger if the innovation is more aligned with regulations. While the growth of individual firms can contribute to overall economic growth, it might instead represent only an increase in their market share. The model in Section 2 implies the latter. According to Proposition 3, in a dynamic setting, incumbent firms face additional incentives to adopt regulation-driven innovations, because these innovations help them deter competitors and potentially increase their market power. I examine these implications empirically using the measure of firm-level innovation-regulation alignment.

Methodology and Data

Because firm-level innovation-regulation alignment is strongly increasing in firm size, as shown in Figure 4, it is important to ensure that fluctuations in size are not driving the relationship between innovation-regulation alignment and economic outcomes in this analysis. Following Kogan et al. (2017), I scale the levels of innovation-regulation alignment by firm size as following:

$$\tilde{\xi}_{f,t} = \frac{\xi_{f,t}}{A_{f,t}}, \tag{28}$$

where $A_{f,t}$ is total assets of firm f in year t. I also control for various measures of firm size in the empirical specifications.

As a traditional measure of innovative output, citation-weighted patent counts reflect the intrinsic (or technological) value of innovation (Abrams et al., 2013). As discussed in Section 5.1, this value is less likely driven by the extent to which the patent is aligned with regulation, whereas it has been demonstrated to be linked to firm performance (Bloom and Van Reenen, 2002). Therefore, I include a measure of citation-weighted patent counts in this analysis. The measure is constructed as follows:

$$\tilde{\theta}_{f,t} = \frac{1}{A_{f,t}} \sum_{i \in P_{f,t}} (1 + \tilde{C}_i), \tag{29}$$

where $P_{f,t}$ is the set of patents assigned to firm f in year t, and $\tilde{C}$ is truncation-adjusted forward citations of patent i from equation (24). For similar considerations regarding firm size, the citation-weighted patent count is also scaled by total assets of firm f in year t.

In this analysis, I assess two categories of firms outcomes: growth in size and market power. The empirical specification is:

$$logY_{f,t+\tau} - logY_{f,t} = \alpha_\tau + \beta_\tau \tilde{\xi}_{f,t} + \gamma_\tau \tilde{\theta}_{f,t} + \delta_\tau W_{f,t} + \nu_{f,t+\tau}, \tag{30}$$

where Y is one of the firm outcome variables, including four indicators of firm growth:

(a) profits, (b) output, (c) capital stock, and (d) employment; and two indicators of market power: (e) market share and (f) markup; the vector W includes the log values of capital stock and number of employees to control for firm size, the lagged value of the dependent variable, industry (SIC-4) fixed effects, and year fixed effects. Given that firms in the same industry are generally subject to the same regulations, this specification focuses on the variation in how firms subject to the same regulations adapt their innovation activities to regulations. In alternative specifications, I replace industry fixed effects with industry-specific year fixed effects or firm fixed effects to account for unobservable factors at the industry-year or firm level. Standard errors are clustered by both firm and year. I consider horizon τ of one to five years.

The original dataset covers all firms in the CRSP/Compustat merged database from 1976 to 2020, including 278,929 firm-year observations. I merge this dataset with the data on firm-level innovation-regulation alignment. If firm f was granted no patents in year t, I set both the scaled innovation-regulation alignment $\tilde{\xi}_{f,t}$ and the scaled citation-weighted patent count $\tilde{\theta}_{f,t}$ to zero. I omit the industries in which no firms were granted a patent in the sample, since the analysis focuses on within-industry variation.[13] That results in 275,977 firm-year observations, covering 25,607 unique firms from 414 SIC-4 industries. Of those firms, 7,279 firms (28 percent) were granted at least one patent during this time frame, and 2,938 firms (11 percent) have a positive innovation-regulation alignment value in at least one year. To minimize the impact of outliers in the analysis, I trim the data at the one percent level for all variables.[14]

The four indicators of firm growth in size are defined as follows: profits are sales (Compustat: SALE) minus cost of goods (Compustat: COGS), deflated by the CPI; output is sales plus change in inventories (Compustat: INVT), deflated by the CPI; capital stock (Compu-

[13] There are 35 SIC-4 industries that never received a patent in the sample, such as Prepared Fresh or Frozen Fish and Seafoods (2092), Screw Machine Products (3451), and Railroad Switching and Terminal Establishments (4013).

[14] Given that the innovation-regulation alignment variable ($\tilde{\xi}_{f,t}$) and the citation-weighted patents variable ($\tilde{\theta}_{f,t}$) contains many zero values, the trimming only discards extreme values above the 99th percentile for those two variables.

stat: PPEGT) is deflated by the non-residential private fixed investment price index from the National Income and Product Accounts provided by the Bureau of Economic Analysis; and employment is number of employees (Compustat: EMP).

As an indicator of market power, I calculate market share as firm f's share of sales in the industry's (SIC-4) total sales in year t. Another common indicator of market power is markup, which measures how much firms are able to price their goods above marginal cost. I estimate markups for the firms under analysis using the production approach from De Loecker et al. (2020). The markup is defined as the wedge between a variable input's expenditure share in revenue and that input's output elasticity:

$$M_{f,t} = \eta^{v}_{s,t} \frac{P_{f,t} Q_{f,t}}{P^{v}_{f,t} V_{f,t}}, \tag{31}$$

where η^v is the output elasticity of the variable input V, $P_{f,t}Q_{f,t}$ is firm f's revenue in year t, and $P^v_{f,t}V_{f,t}$ is the cost of the variable input. I use De Loecker et al. (2020)'s estimate of time-varying and sector-specific (NAICS-2) output elasticity for $\eta_{s,t}$, as well as observed revenue and input expenditure from Compustat (SALE and COGS) in the estimation. Appendix E.1 presents summary statistics for the data used in the firm-level analysis.

Estimation Results

Table 5 shows the estimated coefficients β_τ using the baseline specification. Consistent with the model implications, we see that innovation-regulation alignment is positively associated with firm growth in terms of profits, output, capital, and employment. Over a five-year horizon, a one standard deviation increase in innovation-regulation alignment is associated with a 0.7 percentage-point increase in profits and output growth, a 0.5 percentage-point increase in capital investment growth, and a 0.9 percentage-point increase in employment growth, on average.[15] A median-sized firm that is perfectly aligned with one additional CFR

[15] Note that the standard deviation (0.002) is calculated across all firm-year observations under analysis, including firms with no patent in a year. For firm-year observations with a positive innovation-regulation alignment value, a one standard deviation increase is 0.007, nearly four times than that of the entire sample,

part in its patented innovations tends to grow 1.0 percentage point faster in profits and output, 0.7 percentage point faster in capital investment, and 1.3 percentage points faster in employment, all else being equal.[16]

We also observe that innovation-regulation alignment is positively associated with growth in market share and markup. A one standard deviation increase in a firm's innovation-regulation alignment is associated with a 0.5 percentage-point increase in market share growth and a 0.4 percentage-point increase in markup growth over a five-year horizon. Equivalently, if a median-sized firm gets aligned with one additional CFR part, on average, its market share and markup will grow 0.7 percentage point and 0.6 percentage point faster, respectively.

Table 5: Firm Outcomes and Innovation-Regulation Alignment

	Horizon				
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$
(a) Profit	1.224***	1.639***	2.713***	3.341***	3.499***
	(0.362)	(0.499)	(0.693)	(0.926)	(1.170)
(b) Output	0.812*	1.506***	2.803***	2.449**	3.287***
	(0.407)	(0.492)	(0.749)	(0.960)	(1.032)
(c) Capital	0.468*	0.636	1.608**	1.967**	2.488**
	(0.272)	(0.482)	(0.716)	(0.880)	(1.052)
(d) Employment	1.137***	1.878***	3.017***	3.629***	4.357***
	(0.266)	(0.459)	(0.676)	(0.963)	(1.061)
(e) Market share	0.700	1.618***	2.420***	2.887***	2.557**
	(0.425)	(0.537)	(0.827)	(1.067)	(1.231)
(f) Markup	0.782***	1.206***	1.622***	1.560***	2.120***
	(0.267)	(0.422)	(0.520)	(0.571)	(0.567)

Notes: The table shows the estimated coefficients, β_τ, in equation (30) for $\tau \in \{1, 2, 3, 4, 5\}$. Full estimation results are available in Appendix E.2. Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

so the magnitude of effect can be larger.

[16] I consider a firm with a median number of total assets in the data, which is approximately $350 millions. Being perfectly aligned with one additional CFR part means having an additional $\rho_{i,j} = 1$ and thus a one-unit increase in R_i and $\xi_{f,t}$. Scaled by total assets, that converts to an approximately 0.0029 unit increase in $\tilde{\xi}_{f,t}$.

6.3 Competitors' Growth

While regulation-driven innovation has a positive impact on the innovating firm's economic outcomes, it creates relative disadvantage for the firm's competitors. As a result, I expect that a firm's innovation-regulation alignment is negatively associated with its competitors' growth. To test this hypothesis, I examine the relationship between a firm's innovation-regulation alignment and its competitors' growth, controlling for competitors' innovation-regulation alignment. I define the innovation-regulation alignment of firm f's competitors as:

$$\tilde{\xi}_{I\backslash f,t} = \frac{\sum_{f' \in I\backslash f} \xi_{f',t}}{\sum_{f' \in I\backslash f} A_{f',t}}, \tag{32}$$

where $I\backslash f$ is the set of firm f's competitors, defined as all firms in the same industry (SIC-4) excluding firm f in year t. The empirical specification is similar to equation (30):

$$logY_{I\backslash f,t+\tau} - logY_{I\backslash f,t} = \alpha_\tau + \beta_\tau \tilde{\xi}_{f,t} + +\gamma_\tau \tilde{\theta}_{f,t} + \beta'_\tau \tilde{\xi}_{I\backslash f,t} + \gamma'_\tau \tilde{\theta}_{I\backslash f,t} + \delta_\tau W_{I\backslash f,t} + \nu_{\backslash f,t+\tau}, \tag{33}$$

where $Y_{I\backslash f}$ is one of competitors' economic variables, including (a) profits, (b) output, (c) capital, and (d) employment; $\tilde{\xi}$ is the firm's or its competitors' scaled innovation-regulation alignment; $\tilde{\theta}$ is the firm's or its competitors' citation-weighted patent counts to control for the technological value of innovative output; and the vector W includes the log values of competitors' capital stock and number of employees, the lagged value of the dependent variable Y, industry (SIC-4) fixed effects, and year fixed effects. Descriptive statistics for competitors' variables are available in Appendix F.1.

As shown in Table 6, the estimation results are consistent with the expectation. In general, a firm's innovation-regulation alignment is negatively associated with its competitors' growth in profits, output, and capital, but not employment. If a median-sized firm gets aligned with one additional CFR part in its innovative output, its competitors will experience an approximately 0.4 percentage-point slowdown in their total profits, output, and capital growth. One possible explanation for the insignificant finding for employment is barriers to labor reallocation due to firing costs, which has been well-documented in the literature (Mukoyama and Osotimehin, 2019; Moscoso Boedo and Mukoyama, 2012; Da-Rocha et al., 2019). The existence of firing costs makes it harder for firms to adjust labor (compared to capital investment and output) when encountering cost disadvantages, so we do not see a similar effect of a firm's regulation-driven innovations on its competitors' employment growth.

Table 6: Firm Innovation-Regulation Alignment and Competitors' Growth

	Horizon				
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$
(a) Profit	-0.411	-0.951**	-1.447***	-1.620**	-1.595*
	(0.246)	(0.421)	(0.511)	(0.651)	(0.799)
(b) Output	-0.174	-0.643	-1.152**	-1.483**	-1.540**
	(0.232)	(0.386)	(0.514)	(0.582)	(0.712)
(c) Capital	-0.353	-0.790**	-1.380**	-1.769**	-1.469*
	(0.244)	(0.389)	(0.574)	(0.707)	(0.865)
(d) Employment	-0.069	-0.347	-0.532	-0.812	-0.747
	(0.220)	(0.376)	(0.522)	(0.629)	(0.753)

Notes: The table shows the estimated coefficients, β_τ, in equation (33) for $\tau \in \{1, 2, 3, 4, 5\}$. Full estimation results are available in Appendix F.2. Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

These results have some macroeconomic implications. If regulation-driven innovations benefit only the innovating firm while harming others, then the variation in such innovations could influence aggregate economic outcomes. I explore this in the next section.

7 Macroeconomic Implications of Innovation-Regulation Alignment

To uncover macroeconomic implications of regulation-driven innovations, I first need an economy-wide measure of innovation-regulation alignment. I aggregate the patent-level regulatory alignment measure into a time series index by estimating the following fixed effects regression:

$$R_i = u_{t(i)} + v_{I(i)} + \epsilon_i, \tag{34}$$

where R_i is patent i's regulatory alignment value from equation (23), $u_{t(i)}$ is year-quarter fixed effects based on patent i's grant date, and $v_{I(i)}$ is industry (SIC-3) fixed effects based on the assignee firm's industry. The estimated coefficients on $u_{t(i)}$ constitutes a quarterly index of aggregate innovation-regulation alignment, $\mathcal{R}_t$. All the patents with the industry information are used in the estimation, including 2,368,490 patents. Appendix G plots the quarterly index as well as its growth rates over the period of 1976-2020. The index exhibits a monotonically increasing trend, similar to the trend discussed in Section 4.2.

I examine the impulse responses of macroeconomic variables to an upward shock in the aggregate innovation-regulation alignment using a local projection method (Jordà, 2005). Local projections impose less restrictive assumptions on data dynamics compared to the standard vector autoregression (VAR). This method has been widely used for estimating impulse response functions in the context of text-based time series measures (Shapiro et al., 2022; Caldara et al., 2020; Ahir et al., 2022). The estimation entails a distinct linear regression for each forecast horizon h with the following specification:

$$y_{m,t+h} = \alpha_m^h + \beta_m^h \tilde{\mathcal{R}}_t + \sum_{\tau=1}^{3} \gamma_{m,\tau}^h \tilde{\mathcal{R}}_{t-\tau} + A_m^h \sum_{\tau=0}^{3} Y_{t-\tau} + \varepsilon_{m,t+h}, \tag{35}$$

where y_m is one of the macroeconomic variables: log GDP, log employment, log investment, and log S&P 500; $\tilde{\mathcal{R}}$ is the growth rate of aggregate innovation-regulation alignment, as approximated by $\tilde{\mathcal{R}}_t = log(\mathcal{R}_t) - log(\mathcal{R}_{t-1})$, to separate the potential impact of the increasing quantity of regulations over time; and the matrix Y includes contemporaneous and lagged values of the macroeconomic variables including log GDP, log employment, log investment, log S&P 500, and log CPI. Based on multiple information criteria, I choose three lags for the variables.[17] The impulse response of economic variable y_m to a shock in the growth of

[17] AIC and FPE suggest three lags, while HQIC suggests two lags, and SBIC suggests one. Using two lags instead of three generates similar results.

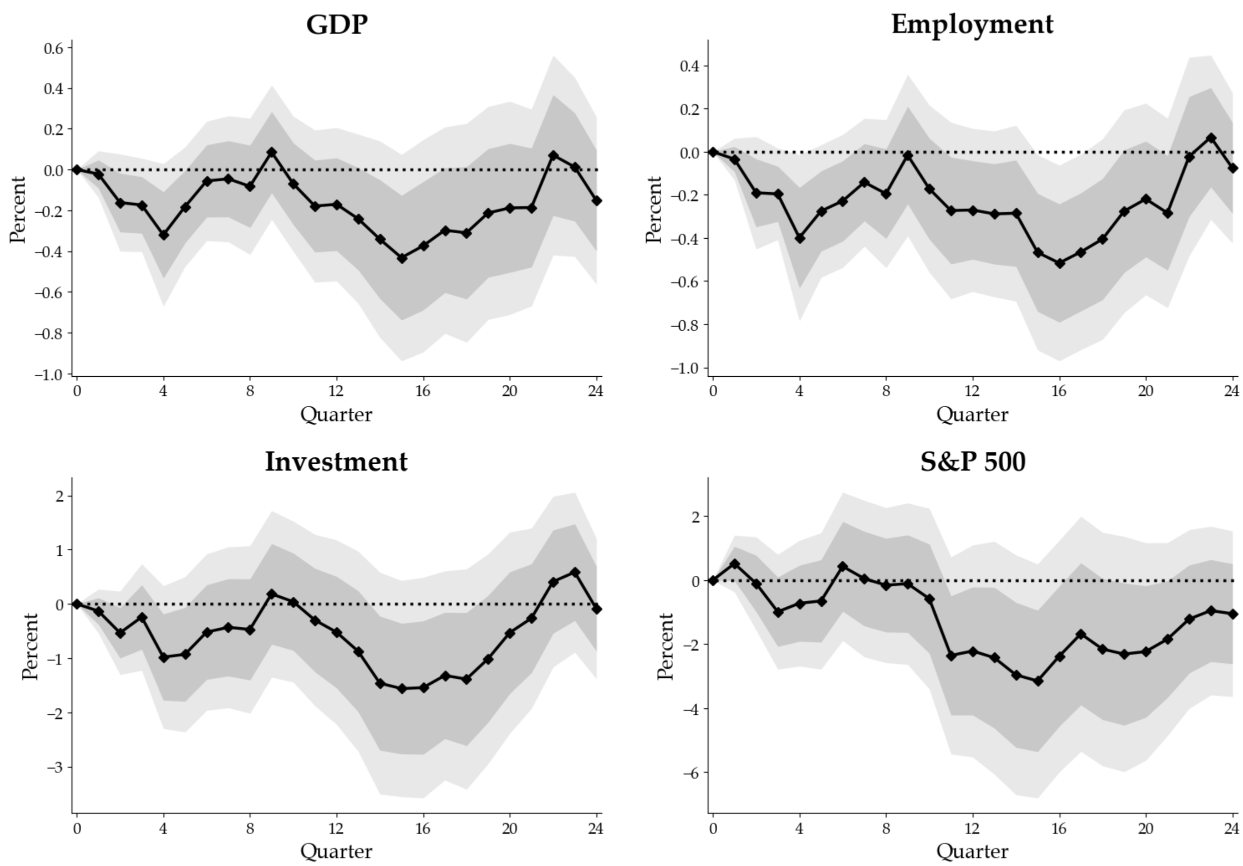
innovation-regulation alignment is given by the estimates of β_m^h. I consider horizons up to 24 quarters after the shock ($h = \{0, 1, ..., 24\}$).

I use quarterly data on real GDP and real gross private domestic investment from the Bureau of Economic Analysis. Employment is the quarterly number of all nonfarm employees reported by the Bureau of Labor Statistics. S&P 500 and CPI are quarterly means of the index values from the S&P Dow Jones Indices LLC and the Bureau of Labor Statistics, respectively.

Figure 5 plots the impulse responses of GDP, employment, investment, and S&P 500 to a one-standard-deviation upward shock in the growth of aggregate innovation-regulation alignment, with point estimates as well as 68 percent and 90 percent confidence bands. The estimates show that a shock to the innovation-regulation alignment growth reduces aggregate output, employment, investment, and stock prices. Although most of the drops are only significant according to the 68 percent confidence band, the magnitude of the effects is noticeable. The maximum drops in output and employment reach 0.4 percent and 0.5 percent, respectively. The potential effects on investment and stock prices are larger, with private investment decreasing by up to 1.6 percent and the S&P 500 index dropping by 3.1 percent after a shock.

These effects are comparable in size to the impact of other macroeconomic shocks. Leading studies using various identification strategies generally suggest that a monetary policy shock equal to 100 basis-point surprise increase in the federal funds rate is associated with a peak drop of 0.6-5.0 percent in output (Ramey, 2016). Barro and Redlick (2011) find that an unanticipated one-percentage-point increase in the average marginal income tax rate lowers GDP by around 0.5 percent. Baker et al. (2016) demonstrate that a 90-point upward shock to their economic policy uncertainty measure (equal in size to the change between the periods before and after the financial crisis) is associated with maximum drops of 1.1 percent in output, 0.4 percent in employment, and 6.0 percent in gross aggregate investment. Therefore, the macroeconomic effects of innovation-regulation alignment are economically significant.

Figure 5: Impulse Responses



Notes: The figures plot impulse response functions to a one-standard-deviation upward shock to the growth of aggregate innovation-regulation alignment. The aggregate innovation-regulation alignment, $\mathcal{R}$, is estimated using equation (35). Shaded areas show 68 percent (dark gray) and 90 percent (light gray) confidence bands.

8 Conclusion

In this paper, I explore regulation-driven innovations—those developed to comply with or circumvent legal and regulatory requirements—and their economic implications. Using text data from U.S. patents issued between 1976 and 2020 and the CFR, I propose a measure of regulatory alignment for regulation-driven innovations based on semantic similarities between patent texts and federal regulations. Consistent with the predictions of a Schumpeterian growth model, regulation-driven innovations identified using the measure move in tandem with the economic value of patents, as well as with firm growth in size and market power. However, aggregating the measure suggests that innovation-regulation alignment is negatively associated with overall economic growth.

Through both theoretical modeling and empirical evidence, this study demonstrates that regulation-driven innovations can provide private gains to firms by reducing regulatory burdens and enhancing their competitive positions. However, these innovations may impede economic growth by increasing barriers to entry, altering resource reallocation, and slowing creative destruction.

While this study highlights the economic impact of government regulations, it is important to acknowledge the societal benefits created by regulations, such as reduced pollution and safe products and workplaces. These societal benefits are not formally considered in this study. Some of the economic costs may be worth paying to achieve the intended social objectives of regulation. However, when designing new regulations or revising existing ones, policymakers should carefully weigh societal benefits against potential economic costs, such as those demonstrated in this study, to avoid unintended economic consequences or unnecessary regulatory burdens. This is particularly important as policymakers strive for a regulatory environment that is responsive to the rapid development of emerging technologies such as artificial intelligence (AI). With the recently increasing demand for AI regulation, policymakers should carefully consider a regulatory approach that not only addresses potential risks posed by these novel technologies but also encourages technological advancement and competition.

This paper focuses on a particular type of innovations—those developed in response to regulations—and studies how they relate to firm dynamics and economic growth. Future work could investigate the causal effects of regulation on the broader technological innovation, examining the innovations contributing to technological advancement and those forgone due to regulatory constraints. Additionally, examining how different forms of regulations—such as command-and-control vs. market-based regulations—impact innovation activities could offer a more nuanced understanding of the interplay between innovation and regulation.

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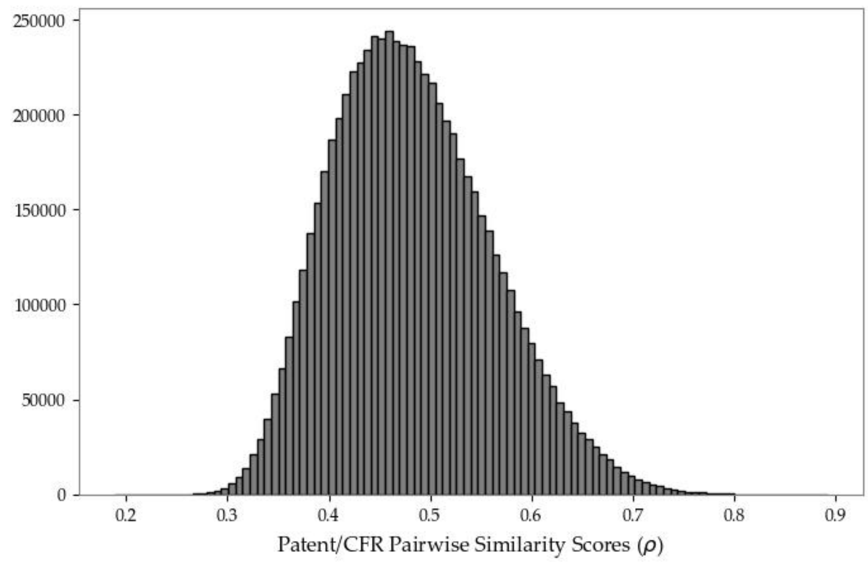
Appendices

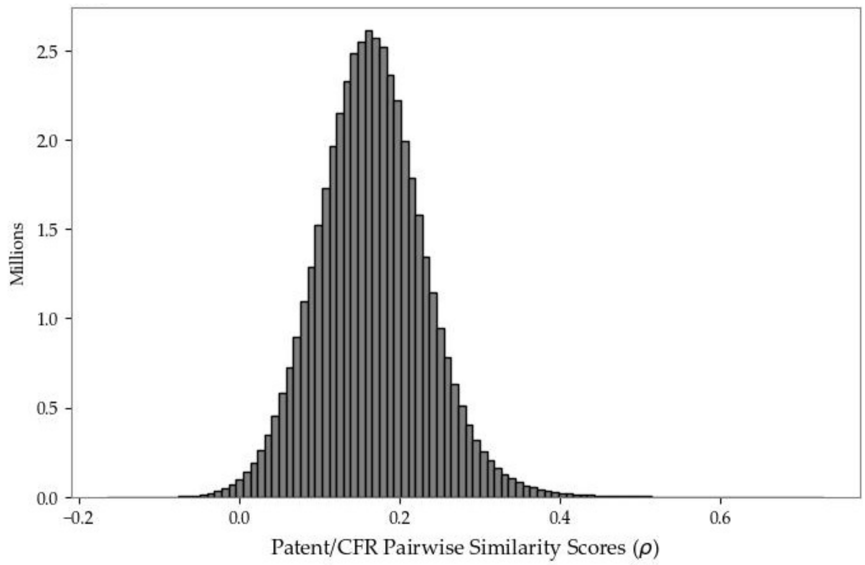
A Distribution of Patent-CFR Pairwise Similarities

A.1 Distribution of Maximum Similarities for All Patents



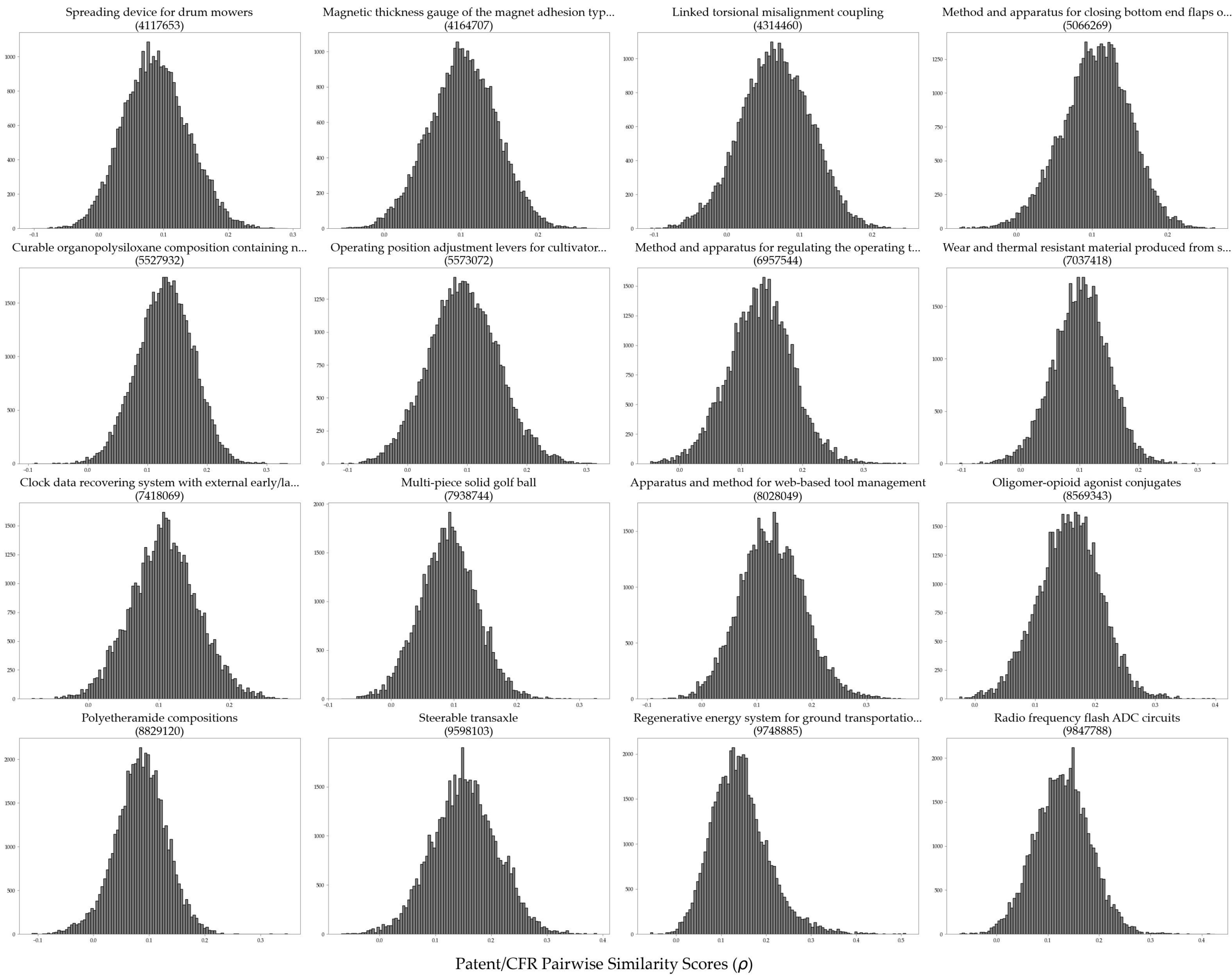
Notes: The figure plots the histogram of the maximum pairwise similarities (ρ) between a patent and the CFR parts published during the patent grant year and the preceding five years for all patents in the sample ($N = 6,912,239$).

A.2 Distribution of Similarities for a Random Sample of Patents



Notes: The figure plots the histogram of all pairwise similarities (ρ) between a patent and the CFR parts published during the patent grant year and the preceding five years for a random sample of 1,000 patents.

A.3 Within-Patent Distribution of Similarities



Notes: The figure plots the histogram of pairwise similarities (ρ) between a randomly selected patent and the CFR parts published during the patent grant year and the preceding five years.

B Descriptive Patterns of Patent Regulatory Alignment

B.1 Regulatory Alignment for Select Technology Classes

CPC Class	Total Patents	Regulatory-Aligned Patents	Share of Regulatory-Aligned Patents	Average R_i
Information and Communication Technology (ICT) Specially Adapted for Specific Application Fields (G16)	10,249	3,188	31%	3.68
Organic Macromolecular Compounds; Their Preparation Or Chemical Working-up; Compositions Based Thereon (C08)	127,864	33,724	26%	1.48
Centrifugal Apparatus Or Machines For Carrying-out Physical Or Chemical Processes (B04)	3,272	811	25%	0.70
Information or Communication Technologies Having an Impact on Other Technology Areas (Y04)	286	66	23%	1.65
Refrigeration Or Cooling; Combined Heating And Refrigeration Systems; Heat Pump Systems; Manufacture Or Storage Of Ice; Liquefaction Solidification Of Gases (F25)	24,178	4,375	18%	1.61
Checking-devices (G07)	34,714	6,208	18%	1.18
Life-saving; Fire-fighting (A62)	7,630	1,297	17%	2.21
Petroleum, Gas Or Coke Industries; Technical Gases Containing Carbon Monoxide; Fuels; Lubricants; Peat (C10)	33,533	5,493	16%	1.14
Dyes; Paints; Polishes; Natural Resins; Adhesives; Compositions Not Otherwise Provided For; Applications Of Materials Not Otherwise Provided For (C09)	50,820	8,321	16%	0.97
Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing (A01)	90,171	14,526	16%	1.18

Notes: This table lists the ten CPC classes with the highest proportions of regulatory-aligned patents over the period from 1976 to 2020. The average R_i represents the average regulatory alignment value of all patents within each CPC class.

C Regulatory Alignment and Patent Value

C.1 Description of Control Variables

Backward citations are the number of patents cited in a patent, measuring its reliance on previous technology (Jaffe and De Rassenfosse, 2019). Backward citation age refers to the average time (i.e., days) between the grant of a patent and the grant of the cited patents. It measures the proximity of the citing patent to the technological frontier, as technologically influential patents are more likely to cite new patents (Higham et al., 2021; Benson and Magee, 2015). Originality quantifies the diversity of technological classifications of a patent's backward citations. As in Trajtenberg et al. (1997); Higham et al. (2021), I define the originality of patent i as:

$$O_i = 1 - \sum_C (P_C^i)^2, \tag{36}$$

where P_C^i is the proportion of the backward citations from patent i to other patents in a technology class C from the Cooperative Patent Classification (CPC) scheme. A larger O_i indicates broader technological roots of the underlying research for patent i.

Grant lag is the time (i.e., days) between the application date and the grant date of a patent. Patents of lower quality are likely to take longer to negotiate and examine and thus associated with a longer grant lag (Higham et al., 2021; Harhoff and Wagner, 2009; Régibeau and Rockett, 2010; Squicciarini et al., 2013). Patent scope, or information content of a patent, is measured by the number of CPC classes under which the patent is classified. The number of independent claims and dependent claim ratio (i.e., number of dependent claims per independent claim) measure the scope of legal rights granted to the patent owner (Higham et al., 2021; De Rassenfosse and Jaffe, 2018; Marco et al., 2019; Lanjouw and Schankerman, 2001; Lanjouw et al., 1998). The length of the first claim and the shortest independent claim reflect claim breadth, as additional words tend to correspond to more limitations to patent claims (Ashtor, 2019; Kuhn and Thompson, 2019; Marco et al., 2019).

C.2 Descriptive Statistics of Patent Variables

C.2.1 Variables for Scientific Value Analysis

Variable	N	Mean	Median	Std. Dev.	Min	Max
Forward citations ($\tilde{C}_i$)	6,900,262	0.74	0.25	2.44	0.00	277.81
Regulatory alignment (R_i)	6,900,262	0.53	0.00	3.94	0.00	861.02
Backward citations	6,900,262	14.93	6.00	57.49	0.00	5,841.00
Backward citation age (thous. days)	6,463,657	5.02	4.01	3.81	0.02	111.11
Originality	6,123,090	0.59	0.66	0.27	0.00	1.00
Grant lag (thous. days)	6,900,120	0.99	0.85	0.59	0.00	109.95
CPC number	6,900,262	1.71	1.00	0.96	1.00	24.00
Claim number	6,900,262	15.56	14.00	11.25	1.00	887.00
Independent claim number	6,548,198	2.62	2.00	2.02	0.00	248.00
Dependent claim ratio	6,548,038	6.06	5.00	5.18	0.00	886.00
First claim length	6,548,197	185.09	162.00	133.01	2.00	77,533.00
Independent claim length	6,548,038	163.03	142.00	120.74	1.00	77,533.00

C.2.2 Variables for Economic Value Analysis

Variable	N	Mean	Median	Std. Dev.	Min	Max
Economic value (E_i)	2,368,490	11.09	3.49	30.34	1.73e-4	2,573.78
Regulatory alignment (R_i)	2,368,490	0.54	0.00	4.02	0.00	667.09
Forward citations ($\tilde{C}_i$)	2,368,490	0.87	0.29	3.11	0.00	225.53
Total assets (tril. $)	2,315,437	77.25	33.62	148.28	2.04e-4	3,206.47

C.3 Full Regression Results on Forward Citations

C.3.1 Using all patents

	(1)	(2)	(3)
Regulatory alignment	0.002	-0.002	-0.003
	(0.004)	(0.004)	(0.005)
Backward citations		0.128***	0.134***
		(0.014)	(0.014)
Backward citation age		-0.108***	-0.112***
		(0.010)	(0.009)
Originality		-0.032	-0.049
		(0.040)	(0.041)
Grant lag		0.009	0.025***
		(0.011)	(0.009)
CPC number		0.093***	0.086***
		(0.009)	(0.007)
Claim number		0.178***	0.189***
		(0.024)	(0.028)
Independent claim number		-0.042	-0.050*
		(0.027)	(0.030)
Dependent claim ratio		-0.055**	-0.064***
		(0.013)	(0.015)
First claim length		0.044***	0.037***
		(0.008)	(0.006)
Independent claim length		0.007	0.005
		(0.007)	(0.007)
Technology class FE	YES	YES	YES
Patent year FE	YES	YES	NO
Time trend	NO	NO	YES
N	6,900,262	5,649,030	5,649,030
R^2	0.148	0.206	0.201

Notes: This table shows the estimated coefficients in equation (25). Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

C.3.2 Using patents assigned to publicly traded firms

	(1)	**(2)**	**(3)**
Regulatory alignment	0.001	-0.002	-0.003
	(0.004)	(0.004)	(0.004)
Backward citations		0.127***	0.133***
		(0.017)	(0.017)
Backward citation age		-0.122***	-0.126***
		(0.011)	(0.012)
Originality		-0.023	-0.046
		(0.045)	(0.044)
Grant lag		0.023*	0.038***
		(0.013)	(0.013)
CPC number		0.093***	0.089***
		(0.011)	(0.009)
Claim number		0.180***	0.196***
		(0.033)	(0.037)
Independent claim number		-0.032	-0.046
		(0.033)	(0.035)
Dependent claim ratio		-0.045**	-0.058***
		(0.017)	(0.019)
First claim length		0.054***	0.051***
		(0.009)	(0.007)
Independent claim length		0.001	-0.004
		(0.008)	(0.009)
Technology class FE	YES	YES	YES
Patent year FE	YES	YES	NO
Time trend	NO	NO	YES
N	2,365,659	1,999,904	1,999,904
R^2	0.138	0.191	0.185

Notes: This table shows the estimated coefficients in equation (25), using only patents assigned to publicly traded firms. Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

D Industries with the Highest Innovation-Regulation Alignment

SIC-4	Industry Name	Leading Firms
6111	Federal and Federally-Sponsored Credit Agencies	Federal Home Loan Mortg Corp Federal National Mortga Assn Navient Corp
7363	Help Supply Services	Volt Info Sciences Inc Trueblue Inc Kforce Inc
6792	Oil Royalty Traders	Cross Timbers Royalty Trust
6035	Savings Institutions, Federally Chartered	Rome Bancorp Inc Washington Mutual Inc Harrington West Finl Group
6324	Hospital and Medical Service Plans	Aetna Inc Elevance Health Inc Unitedhealth Group Inc
6099	Functions Related to Depository Banking, Not Elsewhere Classified	Xoom Corp Moneygram International Inc Lml Payment Systems Inc
6200	Security & Commodity Brokers, Dealers, Exchanges & Services	Marketaxess Holding Inc CME Group Inc Intercontinental Exchange
5047	Medical, Dental, and Hospital Equipment and Supplies	Henry Schein Inc Mwi Veterinary Supply Fisons Plc
4513	Air Courier Services	Fedex Corp Airborne Inc Purolator Courier Corp
5912	Drug Stores and Proprietary Stores	Express Scripts Holding Co Omnicare Inc Medco Health Solutions Inc

Notes: The table lists the industries with the highest average per-patent innovation-regulation alignment values over the period of 1976-2020, as well as the top three firms with the highest average per-patent innovation-regulation alignment values within each industry. Per-patent innovation-regulation alignment is calculated as a firm's innovation-regulation alignment in a given year ($\xi_{f,t}$) divided by the number of patents assigned to the firm in that year.

E Firm Growth and Market Power

E.1 Descriptive Statistics of Firm Variables

Variable	N	Mean	Median	Std. Dev.	Min	Max
Innovation-regulation alignment, scaled ($\tilde{\xi}_{f,t}$)	250,345	3.39e-4	0.00	2.22e-3	0.00	0.03
Citation-weighted patent counts ($\tilde{\theta}_{f,t}$)	250,345	9.10e-3	0.00	0.04	0.00	0.40
Profit growth	206,574	0.06	0.05	0.43	-5.70	6.14
Output growth	204,244	0.05	0.04	0.40	-7.17	7.10
Capital growth	194,791	0.11	0.07	0.36	-7.40	8.02
Employment growth	209,093	0.05	0.03	0.35	-9.30	8.39
Market share growth	221,104	0.03	0.01	0.44	-8.87	8.93
Markup growth	210,835	7.06e-4	−1.31e-4	0.29	-4.74	5.04

Notes: Profit, output, capital, employment, TFP, and markup are all in first difference of log, which approximates the percentage change in the variable.

E.2 Full Estimation Results

The following tables show the estimated coefficients in equation (30) for $\tau \in \{1, 2, 3, 4, 5\}$. Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

E.2.1 One-Year Growth ($logY_{f,t+1} - logY_{f,t}$)

	(1) Profit	**(2)** Output	**(3)** Capital	**(4)** Labor	**(5)** Market Share	**(6)** Markup
Reg ($\tilde{\xi}_{f,t}$)	1.224***	0.812*	0.468*	1.137***	0.700	0.782***
	(0.362)	(0.407)	(0.272)	(0.266)	(0.425)	(0.267)
Cites ($\tilde{\theta}_{f,t}$)	0.108**	0.010	-0.032	-0.108***	-0.014	0.045
	(0.045)	(0.043)	(0.032)	(0.035)	(0.039)	(0.029)
log($Y_{f,t-1}$)	-0.070***	-0.077***	-0.128***	-0.088***	-0.083***	-0.097***
	(0.004)	(0.004)	(0.008)	(0.008)	(0.005)	(0.004)
log(capital$_{f,t}$)	0.022***	0.019***	0.073***	0.020***	0.020***	0.003
	(0.002)	(0.002)	(0.009)	(0.002)	(0.002)	(0.002)
log(emp$_{f,t}$)	0.040***	0.052***	0.048***	0.056***	0.054***	-0.003
	(0.003)	(0.003))	(0.003)	(0.008)	(0.004)	(0.002)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	152,737	150,689	166,328	164,282	161,285	152,825
R^2	0.037	0.045	0.062	0.029	0.041	0.027

E.2.2 Two-Year Growth ($logY_{f,t+2} - logY_{f,t}$)

	(1) Profit	(2) Output	(3) Capital	(4) Labor	(5) Market Share	(6) Markup
Reg ($\tilde{\xi}_{f,t}$)	1.639***	1.506***	0.636	1.878***	1.618***	1.206***
	(0.499)	(0.492)	(0.482)	(0.459)	(0.537)	(0.422)
Cites ($\tilde{\theta}_{f,t}$)	0.211***	0.030	-0.042	-0.144**	0.013	0.039
	(0.068)	(0.067)	(0.060)	(0.056)	(0.065)	(0.033)
log($Y_{f,t-1}$)	-0.096***	-0.106***	-0.190***	-0.115***	-0.129***	-0.163***
	(0.006)	(0.007)	(0.013)	(0.010)	(0.008)	(0.007)
log($\text{capital}_{f,t}$)	0.031***	0.034***	0.093***	0.035***	0.039***	0.007**
	(0.004)	(0.004)	(0.013)	(0.003)	(0.003)	(0.002)
log($\text{emp}_{f,t}$)	0.044***	0.054***	0.079***	0.050***	0.066***	-0.006**
	(0.005)	(0.006)	(0.004)	(0.012)	(0.006)	(0.003)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	140,649	139,053	152,887	150,847	148,380	138,786
R^2	0.050	0.056	0.087	0.044	0.057	0.053

E.2.3 Three-Year Growth ($logY_{f,t+3} - logY_{f,t}$)

	(1) Profit	(2) Output	(3) Capital	(4) Labor	(5) Market Share	(6) Markup
Reg ($\tilde{\xi}_{f,t}$)	2.713***	2.803***	1.608**	3.017***	2.420***	1.622***
	(0.693)	(0.749)	(0.716)	(0.676)	(0.827)	(0.520)
Cites ($\tilde{\theta}_{f,t}$)	0.336***	0.116	-0.041	-0.123*	0.092	0.082*
	(0.086)	(0.076)	(0.084)	(0.072)	(0.084)	(0.046)
log($Y_{f,t-1}$)	-0.116***	-0.133***	-0.222***	-0.133***	-0.169***	-0.219***
	(0.008)	(0.008)	(0.016)	(0.011)	(0.009)	(0.008)
log($\text{capital}_{f,t}$)	0.036***	0.044***	0.091***	0.045***	0.055***	0.008***
	(0.005)	(0.005)	(0.016)	(0.005)	(0.005)	(0.002)
log($\text{emp}_{f,t}$)	0.045***	0.056***	0.101***	0.042***	0.074***	-0.007***
	(0.005)	(0.006)	(0.006)	(0.013)	(0.007)	(0.003)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	127,849	126,403	138,351	136,541	134,504	126,270
R^2	0.062	0.068	0.102	0.057	0.076	0.081

E.2.4 Four-Year Growth ($logY_{f,t+4} - logY_{f,t}$)

	(1) Profit	(2) Output	(3) Capital	(4) Labor	(5) Market Share	(6) Markup
Reg ($\tilde{\xi}_{f,t}$)	3.341***	2.449**	1.967**	3.629***	2.887***	1.560***
	(0.926)	(0.960)	(0.880)	(0.963)	(1.067)	(0.571)
Cites ($\tilde{\theta}_{f,t}$)	0.450***	0.271***	0.029	-0.090	0.121	0.099*
	(0.103)	(0.092)	(0.098)	(0.086)	(0.108)	(0.053)
log($Y_{f,t-1}$)	-0.133***	-0.158***	-0.262***	-0.138***	-0.204***	-0.270***
	(0.009)	(0.010)	(0.018)	(0.015)	(0.011)	(0.009)
log($\text{capital}_{f,t}$)	0.042***	0.055***	0.101***	0.054***	0.067***	0.009***
	(0.007)	(0.007)	(0.019)	(0.006)	(0.006)	(0.003)
log($\text{emp}_{f,t}$)	0.043***	0.057***	0.120***	0.024	0.082***	-0.009***
	(0.006)	(0.008)	(0.007)	(0.019)	(0.008)	(0.003)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	116,378	115,176	125,456	123,892	122,201	114,995
R^2	0.072	0.081	0.115	0.067	0.095	0.113

E.2.5 Five-Year Growth ($logY_{f,t+5} - logY_{f,t}$)

	(1) Profit	(2) Output	(3) Capital	(4) Labor	(5) Market Share	(6) Markup
Reg ($\tilde{\xi}_{f,t}$)	3.399***	3.287***	2.488**	4.357***	2.557**	2.120***
	(1.170)	(1.032)	(1.052)	(1.061)	(1.231)	(0.567)
Cites ($\tilde{\theta}_{f,t}$)	0.541***	0.299***	0.063	-0.078	0.165	0.118**
	(0.105)	(0.097)	(0.109)	(0.097)	(0.116)	(0.051)
log($Y_{f,t-1}$)	-0.144***	-0.177***	-0.292***	-0.139***	-0.239***	-0.302***
	(0.010)	(0.011)	(0.022)	(0.018)	(0.012)	(0.011)
log($\text{capital}_{f,t}$)	0.047***	0.062***	0.108***	0.064***	0.080***	0.009***
	(0.008)	(0.008)	(0.023)	(0.008)	(0.007)	(0.003)
log($\text{emp}_{f,t}$)	0.038***	0.054***	0.130***	-0.002	0.087***	-0.009**
	(0.008)	(0.009)	(0.008)	(0.023)	(0.009)	(0.003)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	106,107	105,081	113,998	112,582	111,220	104,811
R^2	0.081	0.093	0.124	0.080	0.116	0.133

F Competitors' Growth

F.1 Descriptive Statistics of Competitors' Variables

Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Competitors' innovation-regulation alignment, scaled ($\tilde{\xi}_{I\setminus f,t}$)	250,290	1.09e-3	0	2.31e-3	0	0.02
Competitors' citation-weighted patent counts ($\tilde{\theta}_{I\setminus f,t}$)	250,290	7.57e-3	9.52e-4	0.01	0	0.07
Competitors' profit growth	222,715	0.05	0.05	0.27	-5.53	7.37
Competitors' output growth	204,075	0.03	0.04	0.26	-6.41	6.17
Competitors' capital growth	198,392	0.06	0.06	0.27	-6.06	8.38
Competitors' employment growth	210,878	0.02	0.02	0.26	-5.19	6.47

Notes: Profit, output, capital, and employment are all in first difference of log, which approximates the percentage change in the variable.

F.2 Full Estimation Results

The following tables show the estimated coefficients in equation (33) for $\tau \in \{1, 2, 3, 4, 5\}$. Standard errors in parentheses. ***=statistically significant at $p < 0.01$. **=statistically significant at $p < 0.05$. *=statistically significant at $p < 0.1$.

F.2.1 One-Year Growth ($logY_{I\setminus f,t+1} - logY_{I\setminus f,t}$)

	(1) Profit	**(2)** Output	**(3)** Capital	**(4)** Labor
Reg ($\tilde{\xi}_{f,t}$)	-0.411	-0.174	-0.353	-0.069
	(0.246)	(0.232)	(0.244)	(0.220)
Cites ($\tilde{\theta}_{f,t}$)	0.007	0.010	0.011	-0.005
	(0.020)	(0.022)	(0.020)	(0.020)
$\tilde{\xi}_{I\setminus f,t}$	-2.392	-1.947	-3.391	0.662
	(1.931)	(1.450)	(2.619)	(1.499)
$\tilde{\theta}_{I\setminus f,t}$	0.616	-0.180	0.742*	0.035
	(0.391)	(0.337)	(0.410)	(0.389)
$\log(Y_{I\setminus f,t-1})$	-0.067***	-0.159***	-0.004	0.019
	(0.011)	(0.016)	(0.015)	(0.016)
$\log(\text{capital}_{I\setminus f,t})$	-0.007	0.042***	-0.094***	0.018**
	(0.010)	(0.008)	(0.020)	(0.008)
$\log(\text{emp}_{I\setminus f,t})$	0.007	0.075***	0.038***	-0.113***
	(0.013)	(0.010)	(0.009)	(0.020)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	166,569	153,206	167,290	165,216
R^2	0.107	0.117	0.086	0.081

F.2.2 Two-Year Growth ($logY_{I\backslash f,t+2} - logY_{I\backslash f,t}$)

	(1) Profit	**(2)** Output	**(3)** Capital	**(4)** Labor
Reg ($\tilde{\xi}_{f,t}$)	-0.951**	-0.643	-0.790**	-0.347
	(0.421)	(0.386)	(0.389)	(0.376)
Cites ($\tilde{\theta}_{f,t}$)	-0.005	-0.010	-0.030	-0.021
	(0.028)	(0.030)	(0.030)	(0.030)
$\tilde{\xi}_{I\backslash f,t}$	-0.518	-1.338	-2.770	3.055*
	(2.133)	(1.872)	(2.680)	(1.731)
$\tilde{\theta}_{I\backslash f,t}$	0.613	0.040	0.827	0.084
	(0.554)	(0.501)	(0.588)	(0.564)
$\log(Y_{I\backslash f,t-1})$	-0.106***	-0.175***	-0.030*	0.014
	(0.014)	(0.021)	(0.017)	(0.018)
$\log(\text{capital}_{I\backslash f,t})$	-0.018	0.027**	-0.151***	0.027***
	(0.012)	(0.011)	(0.024)	(0.009)
$\log(\text{emp}_{I\backslash f,t})$	-0.009	0.035**	0.060***	-0.183***
	(0.017)	(0.015)	(0.013)	(0.026)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	153,297	141,392	153,486	151,829
R^2	0.159	0.155	0.147	0.142

F.2.3 Three-Year Growth ($logY_{I\backslash f,t+3} - logY_{I\backslash f,t}$)

	(1) Profit	**(2)** Output	**(3)** Capital	**(4)** Labor
Reg ($\tilde{\xi}_{f,t}$)	-1.447***	-1.152**	-1.380**	-0.532
	(0.511)	(0.514)	(0.574)	(0.522)
Cites ($\tilde{\theta}_{f,t}$)	0.028	0.019	0.035	0.013
	(0.033)	(0.040)	(0.038)	(0.040)
$\tilde{\xi}_{I\backslash f,t}$	1.912	1.090	-2.652	5.838***
	(2.587)	(2.445)	(3.154)	(1.887)
$\tilde{\theta}_{I\backslash f,t}$	0.236	-0.114	1.036	-0.037
	(0.643)	(0.637)	(0.625)	(0.675)
$\log(Y_{I\backslash f,t-1})$	-0.149***	-0.207***	-0.025	0.014
	(0.020)	(0.021)	(0.021)	(0.017)
$\log(\text{capital}_{I\backslash f,t})$	-0.035***	0.013	-0.232***	0.040***
	(0.013)	(0.011)	(0.033)	(0.012)
$\log(\text{emp}_{I\backslash f,t})$	-0.016	0.015	0.075***	-0.259***
	(0.016)	(0.017)	(0.015)	(0.026)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	138,893	128,360	138,768	137,418
R^2	0.213	0.209	0.201	0.196

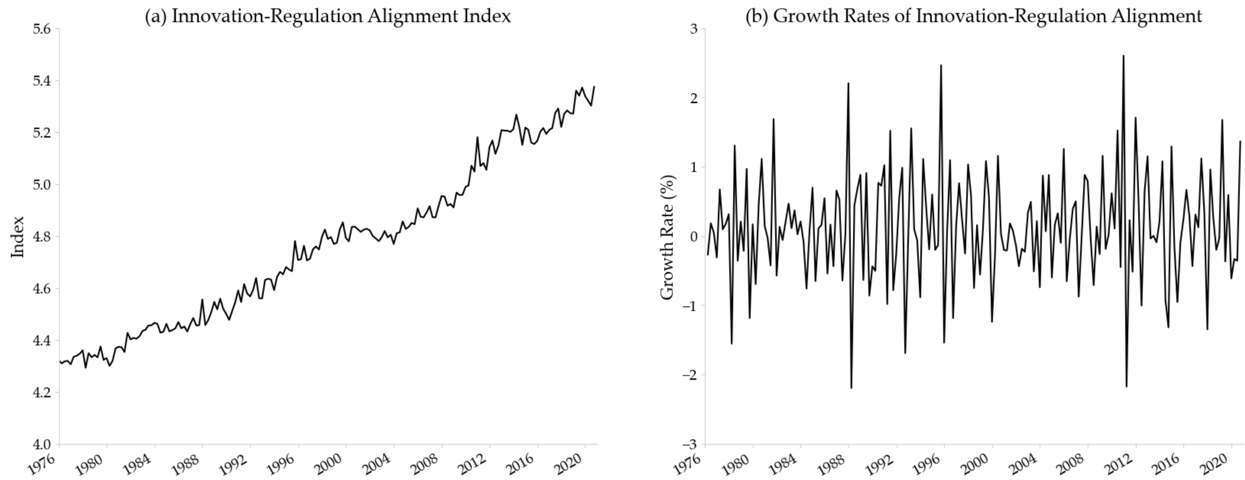
F.2.4 Four-Year Growth ($logY_{I\setminus f,t+4} - logY_{I\setminus f,t}$)

	(1) Profit	**(2)** Output	**(3)** Capital	**(4)** Labor
Reg ($\tilde{\xi}_{f,t}$)	-1.620**	-1.483**	-1.769**	-0.812
	(0.651)	(0.582)	(0.707)	(0.629)
Cites ($\tilde{\theta}_{f,t}$)	0.075*	0.077*	0.077	0.068
	(0.044)	(0.042)	(0.046)	(0.049)
$\tilde{\xi}_{I\setminus f,t}$	3.868	3.567	-1.356	9.010***
	(2.740)	(2.392)	(3.558)	(2.309)
$\tilde{\theta}_{I\setminus f,t}$	0.085	-0.252	0.962	-0.337
	(0.731)	(0.709)	(0.697)	(0.715)
$\log(Y_{I\setminus f,t-1})$	-0.194***	-0.240***	-0.038	0.004
	(0.023)	(0.021)	(0.023)	(0.017)
$\log(\text{capital}_{I\setminus f,t})$	-0.040**	0.007	-0.284***	0.049***
	(0.016)	(0.012)	(0.032)	(0.014)
$\log(\text{emp}_{I\setminus f,t})$	-0.033*	-0.015	0.080***	-0.323***
	(0.019)	(0.020)	(0.016)	(0.028)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	126,006	116,881	125,688	124,740
R^2	0.258	0.256	0.251	0.247

F.2.5 Five-Year Growth ($logY_{I\setminus f,t+5} - logY_{I\setminus f,t}$)

	(1) Profit	**(2)** Output	**(3)** Capital	**(4)** Labor
Reg ($\tilde{\xi}_{f,t}$)	-1.595*	-1.540**	-1.469*	-0.747
	(0.799)	(0.712))	(0.865)	(0.753)
Cites ($\tilde{\theta}_{f,t}$)	0.129**	0.122**	0.133**	0.110**
	(0.049)	(0.051)	(0.053)	(0.052)
$\tilde{\xi}_{I\setminus f,t}$	6.049*	6.021**	-0.410	11.041***
	(3.078)	(2.677)	(4.167)	(2.730)
$\tilde{\theta}_{I\setminus f,t}$	0.234	-0.444	1.256	-0.333
	(0.844)	(0.766)	(0.776)	(0.833)
$\log(Y_{I\setminus f,t-1})$	-0.233***	-0.254***	-0.055**	-0.005
	(0.023)	(0.022)	(0.023)	(0.017)
$\log(\text{capital}_{I\setminus f,t})$	-0.054***	-0.016	-0.331***	0.057***
	(0.018)	(0.013)	(0.035)	(0.016)
$\log(\text{emp}_{I\setminus f,t})$	-0.045**	-0.042*	0.082***	-0.383***
	(0.021)	(0.024)	(0.017)	(0.032)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	114,600	106,561	114,041	113,475
R^2	0.302	0.300	0.296	0.291

G Aggregate Innovation-Regulation Alignment



Notes: Panel (a) plots the quarterly aggregate innovation-regulation alignment index, $\mathcal{R}_t$, estimated from equation (34). Panel (b) plots the growth of aggregate innovation-regulation alignment, as approximated by $\tilde{\mathcal{R}}_t = log(\mathcal{R}_t) - log(\mathcal{R}_{t-1})$.