COMPETING EFFECTS OF INCOME INEQUALITY ON CORPORATE INNOVATION: INCENTIVE AND DEPRIVATION

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE UNIVERSITY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN

BUSINESS ADMINISTRATION

July 2024

By

Hyeonjo Kim

Dissertation Committee:

S. Ghon Rhee, Chairperson
Qianqiu Liu
Jiakai Chen
Susanne Still
Inessa Love

Keywords: Income inequality, innovation, motivation, relative deprivation, sustainability

ACKNOWLEDGMENTS

I am profoundly grateful to my committee members for their guidance, patience, and wisdom: Dr. S. Ghon Rhee, Dr. Qianqiu Liu, Dr. Jiakai Chen, Dr. Susanne Still, and Dr. Inessa Love. Dr. S. Ghon Rhee has been an exceptional role model, fostering in me an enduring curiosity and a deep passion for research. His dedication and steadfast support have profoundly shaped my approach to academic inquiry. Dr. Qianqiu Liu has been a constant source of encouragement and insightful academic advice throughout my studies. His mentorship has been instrumental in my development as a researcher. Dr. Jiakai Chen's generosity in sharing his knowledge has provided invaluable guidance on both theoretical and practical aspects of research. Dr. Susanne Still has inspired me to view the financial market from a fresh and innovative perspective. Dr. Inessa Love has offered insightful and constructive feedback, greatly enhancing the quality of my research.

I am also indebted to many Shidler faculty for their training, support, and advice. I extend my gratitude to Dr. Wei (Victor) Huang, Dr. Jing Ai, Dr. Hua Chen, Dr. Yifan Chen, Dr. Joon Ho Kim, Dr. Nimesh Patel, Dr. Tray Spilker, and Professor Benjamin Bystrom. Special thanks to Dr. Thayanan Phuaphanthong from the Shidler Ph.D. Program for her continuous support and guidance during my Ph.D. journey. I also appreciate the support and insights of the faculty and staff of the Hawai‘i EPSCoR Project, especially Dr. Sukhwa Hong, Dr. Jason Leigh, Michelle Choe, and Shivani Tanaka.

I am equally grateful to my cohorts and colleagues for their friendship and support: Murat Arabaci, Summer Lee, Anna Jeong, Matthew Hinton, Bruce Barnes, Nicole Siegal, Hosuk Choi, Shannon Tran, Adib Rahman, Le Thanh Binh, Cheol-Kon Park, Dongkyu Park, Younghan Lee, Min-Jung Kim, Hamid Bouaicha, Rangrang Zheng, and Iván Rivadeneyra Camino.

Lastly, I owe profound thanks to both sides of my family in South Korea for their unwavering support and belief in my dreams. My deepest gratitude goes to my wife, Soeun, and my two sons, Siwoo and Sunwoo, for their tremendous understanding and faith in me. Your love and encouragement have been my greatest strength.

ABSTRACT

This study examines the effect of state income inequality on corporate innovation, focusing on its psychological dimensions. Income inequality is characterized by monetary incentives and relative deprivation. I investigate how these two characteristics of income inequality influence employee motivations, which in turn affects innovation quantity and quality. While monetary incentives boost innovation quantity, relative deprivation primarily hampers innovation quality. However, even when relative deprivation among employees remains low, income inequality can still positively impact both innovation quantity and quality. Policies aimed at reducing deprivation can enhance corporate innovation and contribute to social sustainability.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

Innovation plays a pivotal role in driving economic growth. The increasing income inequality in recent years could potentially hinder this growth [Deininger and Squire (1997), Cingano (2014)]. In the United States, income inequality has doubled over the past 50 years, coinciding with a two-fold increase in labor productivity, whereas real household income has remained stagnant. This deepening labor market polarization has led to uncertainties regarding the sustainability of economic growth. Moreover, extant literature reveals that higher income inequality has a complex relation with corporate innovation.

This study focuses on the psychological dimensions of income inequality to elucidate its relation with corporate innovation. According to Ku and Salmon (2012), income inequality may instigate two distinct behavioral incentives that influence employees' work efforts and thereby affect their productivity: encouragement and discouragement. Income inequality exhibits ambivalent characteristics that encompass both monetary incentives and relative deprivation. In this context, I explore the nature of income inequality and its potential impact on employees' motivational status, which ultimately influences corporate innovation. Monetary incentives encourage employees to work harder, resulting in more innovative outcomes. Conversely, the experience of deprivation can discourage employees, leading to less innovative outputs.

Further behavioral studies explain how motivational status bridges monetary incentives and relative deprivation with corporate innovation. Ryan and Deci (1985, 2000) examine the two motivation types: extrinsic and intrinsic. Extrinsic motivation is derived from sparable outcomes of work and can be linked to monetary incentives. Meanwhile, intrinsic motivation is derived from one's interest in and enjoyment of work and can be linked to relative deprivation. Furthermore, extrinsic motivation is more aligned with innovation quantity, while intrinsic

motivation is more aligned with innovation quality. Cerasoli, Nicklin, and Ford (2014) find that extrinsic motivation is a better predictor of performance quantity, while intrinsic motivation matters more for performance quality.

Measuring income inequality itself poses several challenges. Although several measures of income inequality exist, each focuses on different aspects of inequality in a state. Thus, these measures may not exhibit a high correlation with one another (Frank 2014). Previous studies find two reasons why the relation between income inequality and innovation is ambiguous. First, income inequality indices may not be highly correlated because they estimate income inequality from different perspectives. Second, the effects of the two inherent characteristics of income inequality on individual motivation may conflict with each other. Additionally, the income inequality characteristics may interact with the two motivation types. Bénabou and Tirole's (2003, 2006) theoretical framework demonstrates how a combination of monetary incentives, deprivation, and the interplay between these motivations contributes to corporate innovation.

Because high-quality firm-level income inequality measures are unavailable, I use state-level income inequality for the empirical analysis focusing on the relation between state-level income inequality and firm-level innovation. Furthermore, to address the heterogeneity of income inequality measures, I establish a connection between the ambivalent psychological characteristics of income inequality and corporate innovation.

This study has three main findings. First, monetary incentives that increase extrinsic motivation lead to higher innovation levels. Second, relative deprivation diminishes intrinsic motivation and undermines innovation quality. Third, even when employees experience relative deprivation, income inequality contributes to both quantitative and qualitative corporate innovation if maintained at lower levels [Bénabou and Tirole (2003, 2006)]. Overall, the study's

findings address the mixed relations between income inequality and innovation found in the existing literature by framing them within Bénabou and Tirole's (2006) model. These mixed results often stem from a focus solely on either the positive or negative aspects of income inequality or the use of diverse measures that may not exhibit high correlation. Bénabou and Tirole's (2006) model accommodates a diverse combination of the two motivation types that influence innovation outcomes by facilitating improvements or hindering progress.

This study has three major contributions. First, this study is the first to examine how income inequality can both stimulate and hinder corporate innovation through two distinct motivational channels: extrinsic and intrinsic. The extrinsic channel connects monetary incentives with enhanced innovation, while the intrinsic channel links relative deprivation with reduced innovation. The relation between income inequality and corporate performance is complex, and this complexity arises from psychological factors resulting from income inequality. Drawing on psychological literature [Stouffer, Lumsdaine, Lumsdaine, Williams, Smith, Janis, Star, and Cottrell (1949), Stouffer, Suchman, DeVinney, Star, and Williams (1949), Stouffer (1962), Deci and Ryan (1985), Ryan and Deci (2000)], I extend Bénabou and Tirole's (2006) model by adding relative deprivation to intrinsic motivation. The findings suggest that the impact of income inequality on corporate innovation varies, depending on the state's level of income deprivation. This relation likely results from a sense of relative deprivation, which undermines employees' intrinsic motivation.

Second, this study differs from existing studies that use state income inequality measures, which may not exhibit a high correlation across the sample period (Frank 2014). This study employs a new measure to better understand the relation between innovation and income inequality. Using principal component analysis, I extract the common characteristics of income

inequality measures into a single variable. I find that the correlation between income inequality measures may be low and that clustering between the top-income shares and broad measures of income inequality is possible. This study provides further insights into the findings of Aghion, Akcigit, Bergeaud, Blundell, and Hemous (2018), who demonstrate a positive correlation between innovation and top-income shares but not with broad income inequality measures. In addition, I quantify deprivation using the difference between a state's income inequality and the average income inequality of the five most similar states in welfare expenditure per capita.

Lastly, this study contributes to the growing body of literature that connects sustainability with corporate performance, supporting the idea that adopting sustainable practices not only drives corporate innovation but also enhances competencies [Nidumolu, Prahalad, and Rangaswami (2009)]. In particular, human-related sustainability perspectives are crucial for fostering corporate innovation, since inventions stem from human capital [Kong, Zhang, and Zhang (2022)], and their success hinges on a deep understanding of consumer behavior [Iyer and Soberman (2016)]. The study's findings suggest that industrial policies aimed at reducing relative deprivation can stimulate both quantitative and qualitative growth in corporate innovation. In addition, the study posits that narrowing the income gap among regions with similar industrial structures can stimulate corporate innovation, going beyond merely addressing regional income disparities. The findings align with those of Ostry, Berg, and Tsangarides (2014), who suggest that well-designed redistribution policies can bolster economic growth. Notably, policies aimed at alleviating relative deprivation do not undermine monetary incentives. Instead, fair policies enhance social sustainability by bolstering employees' morale and fostering both extrinsic and intrinsic motivation.

The remainder of this paper is organized as follows. Chapter 2 presents a literature

review, and Chapter 3 outlines the theoretical framework and the main hypotheses. Chapter 4 describes the empirical model and key variables. Chapter 5 provides the main results, and Chapter 6 includes the robustness tests. Chapter 7 concludes the study.

CHAPTER 2. LITERATURE REVIEW

Income inequality exhibits two ambivalent psychological characteristics that can encourage or discourage employees [Ku and Salmon (2012)]. First, the encouraging aspect of income inequality is often perceived as a form of monetary incentive. Existing literature predominantly views income inequality through the lens of monetary incentives [Mueller, Ouimet, and Simintzi (2017), Miao, Zhang, and Zheng (2020)]. Monetary incentives positively impact the economy by enhancing productivity, suggesting that corporate innovation can be fostered through monetary incentives that address income inequality. Thus, these studies primarily focus on the extrinsic dimension of motivation.

The discouraging effect of income inequality on innovation can be explained through the concept of relative deprivation. Relative deprivation refers to a sense of being disadvantaged compared to a reference group [Stouffer et al. (1949), Stouffer et al. (1949), Stouffer (1962)], resulting in feelings of resentment, anger, and entitlement [Pettigrew (2015)]. Prior literature describes relative deprivation not only in terms of income but also in terms of one's position within the income distribution [Runciman (1966), Yitzhaki (1979), Kakwani (1984), Deaton (2001)], suggesting its potential to incite political activism due to its societal ramifications. Relative deprivation stems from the perception of social injustice arising from the unequal distribution of resources, and individuals experiencing deprivation may advocate for political or policy changes regarding income inequality. Moreover, the sense of deprivation induced by income inequality is closely related to intrinsic motivation. Although intrinsic motivation is indirectly linked to monetary remuneration, Deckop and Cirka (2000) demonstrate that unfair compensation schemes can undermine it, particularly in the context of merit-based pay systems.

Monetary incentives and relative deprivation are closely linked to extrinsic and intrinsic

motivations, respectively. While extrinsic motivation is derived from monetary compensation, leading to increased quantitative outcomes, intrinsic motivation arises from one's interest in and enjoyment of an activity rather than external rewards. Bénabou and Tirole (2006) demonstrate that a heterogeneous mix of motivations, including both intrinsic and extrinsic motivations, can lead to either prosocial or antisocial behavior.[1] This finding implies that income inequality as a motivator may not always have a positive effect on economic output and innovation. Several studies on financial rewards support this idea [Deckop and Cirka (2000), Bénabou and Tirole (2003), Manso (2011)]. Following Ryan and Deci (2000), Cerasoli et al. (2014) find that the best outcome is achieved when both motivations work together. They also note that extrinsic motivation is a better predictor of performance quantity, whereas intrinsic motivation is more critical for performance quality.

Figure 1 summarizes the literature review and depicts the relation between income inequality and corporate innovation through the two motivation types. Extrinsic motivation driven by physical compensation can lead to increased quantitative innovation aimed at improving income. Alternatively, intrinsic motivation can foster qualitative innovation through self-determination and interest; although, an unfair compensation system can weaken intrinsic motivation.

[Insert Figure 1 Here]

In addition to the ambivalent characteristics of income inequality, measuring income inequality is crucial for empirical analysis. Income inequality can be measured using top income share and broad income inequality measures. First, Piketty and Saez (2003) utilize top income shares, such as the top 10%, 5%, 1%, 0.5%, 0.1%, and 0.01%, which are widely used as the

[1] Ryan and Deci (1985, 2000) propose self-determination theory and define two different motivation types: intrinsic and extrinsic motivation.

proxies for income inequality owing to their simplicity and intuitive nature [Leigh (2007), Alvaredo (2011), Atkinson, Piketty, and Saez (2011), Chetty, Hendren, Kline, and Saez (2014)]. However, they overlook changes in income across all classes except the upper-income class. To address this, Aghion et al. (2018) use the average income shares from the top 10% to the top 1% to avoid the concentration of the data on the top 1% of income earners.

Second, broad income inequality measures are also commonly used to compensate for the limitations of top income share data. The Gini coefficient, which considers the income distribution across all classes, is one of the most widely used measures. However, comparing Gini coefficients may not be appropriate when the Lorenz curves of the two groups intersect because they have different implications around the intersection point. Another broad measure is the bottom 99% Gini, which supplements the missing information of the top-income share. Because the top percentile income earners represent a small portion of the population but a significantly large share of total income, the income distribution, excluding the top percentile, can better illustrate the level of income inequality in the bottom 99%.[2]

Each income inequality measure offers a unique perspective, highlighting different aspects of income distribution. While strong correlations exist within groups of similar measures, such as those focusing on top income shares or broad income inequality, the correlation between these two groups tends to be weak. This suggests that the relation between innovation, top income shares, and broad income inequality might differ [Aghion et al. (2018)]. To address this, this study uses the first component, which captures the common characteristics of various income inequality measures.

[2] I calculate the Gini coefficient for the bottom 99% using the approximated method introduced by Atkinson et al. (2011): Gini = (1 - TOP1% Share) × Gini99 + TOP1% Share.

CHAPTER 3. THEORETICAL FRAMEWORK

3.1. Simple Motivation Model with Incentive and Deprivation

In this study, I develop a model based on Bénabou and Tirole's (2003, 2006) theory of motivations and incentives to explore how state income inequality relates to corporate innovation.[3] Bénabou and Tirole (2006) explore the intricate motivations behind prosocial behavior by considering factors such as intrinsic altruism, extrinsic incentives, social reputation, and self-image concerns, suggesting a theoretical framework to understand how these motivations interact. They also discuss how altering these motivations can impact individuals' contributions to public goods and suggest avenues for further research to understand the complexities of human behavior.

Following the theoretical framework of pro-social behavior and motivations, I assume that the effect of income inequality on corporate innovation is due to psychological factors related to employees. In the original model, the agent's benefit is a linear combination of intrinsic and extrinsic motivations, and the incentive rate reflects a proportional subsidy for extrinsic motivation. As income inequality is characterized by incentives [Krueger (2002)], and as this research focuses on state-level income inequality, I use an income inequality measure for the monetary incentive rate r in the model. To reflect another characteristic of income inequality (deprivation) derived from income inequality, I add an income deprivation term $r - \bar{r}$ for the intrinsic valuation, where $\bar{r}$ is the average income inequality of the comparison group. If $r - \bar{r} > 0$, the agent experiences relative deprivation. Therefore, relative deprivation $max(0, r - \bar{r})$ proportionally reduces intrinsic motivation. In summary, in this model, I assume that income

[3] Bénabou and Tirole (2006) present three types of motivation in their model: intrinsic, extrinsic, and reputational motivation. However, in this analysis, I concentrate on intrinsic and extrinsic motivations to interpret the social outcome of corporate innovation. The reason for this focus is that intrinsic motivation is closely associated with qualitative aspects of innovation, while extrinsic motivation is linked to quantitative aspects.

inequality within each state acts as an incentive; although, and that income inequality higher than that of the comparison group (or states) causes relative deprivation.[4] The agent's problem is expressed as follows:

$$\max_{i \in I} \underbrace{[v_i\{1 - max(0, r - \bar{r})\}}_{\text{Intrinsic Motivation}} + \underbrace{v_e r]}_{\text{Extrinsic Motivation}} i - C(i). \quad (1)$$

A representative employee in each state has a preference type $v \equiv (v_i, v_e) \in R^2$, where v_i and v_e are intrinsic and extrinsic valuations, respectively. i is the participation level of innovation from a choice set $I \in R$, and $C(i)$ is the utility cost of choosing i. The first-order condition of the agent's problem in terms of i is as follows:

$$v_i\{1 - max(0, r - \bar{r})\} + v_e r - C'(i) = 0. \quad (2)$$

A representative state employee is a contributor who engages in prosocial behavior through active corporate innovation under the following conditions:

$$v_i\{1 - max(0, r - \bar{r})\} + v_e r \ \geq \ C'(i), \quad (3)$$

where the straight boundary line depends on the existence of relative deprivation. When relative deprivation exists, that is, $r - \bar{r} > 0$, the contributor group comprises all agents for which

$$v_i\{1 - (r - \bar{r})\} + v_e r \ \geq \ C'(i). \quad (4)$$

In the absence of relative deprivation, that is, $r - \bar{r} \leq 0$, the contributor group consists of all agents for which

$$v_i + v_e r \ \geq \ C'(i). \quad (5)$$

Figure 2(a) illustrates the effect of income deprivation on agents' motivational valuation mix depending on the presence or absence of relative deprivation. I find that relative deprivation

[4] Mueller et al. (2017) and Miao et al. (2020) find that within-firm pay inequality may act as an incentive to work, based on data from the UK and China.

displaces potential contributors from a group. Based on equations (4) and (5), the distribution of contributors is derived from the two dimensions of monetary incentives and relative deprivation, as shown in Figure 2(b).[5] This quasi-linear relation shows that the two motivational valuations significantly influence the determination of the boundaries between the contributor and non-contributor groups. Therefore, income inequality can lead to either an increase in corporate innovation as a prosocial outcome or a decrease in corporate innovation as an antisocial outcome, depending on the unobservable heterogeneous mix of motivations.

In this model, depending on the level of monetary incentives and relative deprivation from the state's income inequality, the representative state employee can be a contributor or a non-contributor to corporate innovation. Contributions in this model promote corporate innovation and contribute to both quantity and quality of corporate innovation. However, the solution to the agent's problem only distinguishes between those who contribute to corporate innovation and those who do not. The agent's problem does not explicitly consider quantitative and qualitative innovations. For the same reason, although the model assumes that monetary incentives enhance extrinsic motivation, it does not show how monetary incentives affect the quantity of innovation linked to extrinsic motivation. Additionally, despite the assumption that relative deprivation rooted in income inequality weakens intrinsic motivation, it does not explain how it affects innovation quality, which is closely related to intrinsic motivation.

[Insert Figure 2 Here]

3.2. Testable Hypotheses

I propose three testable hypotheses based on the theoretical model.

Hypothesis 1: *Monetary incentives have a positive impact on quantitative innovation.*

[5] Detailed derivation for Figure 2 is in Appendix A.

I use income inequality as a proxy for monetary incentives. Extrinsic motivation is a motivational state derived from external outcomes of work [Ryan and Deci (1985, 2000)]. If employees are compensated for their work through bonuses and salaries, this form of monetary compensation can strengthen extrinsic motivation. Cerasoli et al. (2014) find that extrinsic motivation predicts the quantity of performance. Therefore, extrinsic motivation based on financial compensation can lead to increased innovation, which in turn can improve income. In other words, extrinsic motivation could help address unequal compensation. Thus, if this hypothesis is correct, the presence of extrinsic motivation can be demonstrated.

Hypothesis 2: *Deprivation has a negative impact on qualitative innovation.*

Intrinsic motivation arises from an individual's interest in and enjoyment of their work. Rooted in self-determination and feelings of competence, intrinsic motivation fosters high-quality learning and creativity [Ryan and Deci (1985, 2000)]. Cerasoli et al. (2014) also find that the quality of performance is more influenced by intrinsic motivation. Intrinsic motivation, based on self-determination and interest, can increase qualitative innovation but can be weakened by an unfair compensation system. The negative aspect of income inequality is understood as income deprivation. As employees feel deprived or discouraged by unequal compensation, they may lack intrinsic motivation, potentially leading to less innovative work output in terms of quality. Therefore, intrinsic motivation linked to income deprivation can result in lower innovation quality. If this hypothesis is correct, the existence of intrinsic motivation could be supported.

Hypothesis 3: *Income inequality with low deprivation positively affects quantitative and qualitative innovations.*

By extending Bénabou and Tirole's (2006) model, I find a quasi-linear relation between monetary incentives and relative deprivation to identify the contributor group that generates

more innovative outcomes. A high monetary stimulus contributes to corporate innovation when relative deprivation is below a certain threshold. However, this theoretical framework does not explicitly address whether the contributor group produces more innovative outcomes in terms of both quantity and quality. As the model classifies the contributor group based on a combination of monetary incentives and deprivation, firms within this group are more likely to engage in both quantitative and qualitative innovations.

CHAPTER 4. BASELINE REGRESSION MODEL

4.1. Empirical Model

I employ a two-level hierarchical linear model (HLM) using a restricted maximum likelihood estimation to assess how state-level income inequality relates to firm-level innovation [Raudenbush and Bryk (2002), Greene (2018), Griffin, Li, and Xu (2021a)]. The baseline regression model is as follows:

$$y_{i,j,t+1} = \gamma_j + X'_{i,j,t}\beta + \epsilon_{i,j,t}, \tag{6}$$

$$\gamma_j = W'_j\delta + u_j, \tag{7}$$

where i, j, and t represent the firm, state, and year, respectively. $y_{i,j,t+1}$ represents corporate innovation outcomes such as quantitative and qualitative innovations. $X'_{i,j,t}$ are firm-level control variables whose state-year mean is subtracted, and W'_j are state-level control variables, including the state-year means of the firm-level controls. By subtracting the state-year means from the firm-level controls, the within-state and cross-state effects on firm-level innovation are completely separated. δ contains the state-level relation between W'_j and the state-level intercept term γ_j.

In addition, unlike the ordinary least squares (OLS) model, which assumes that the error term is distributed independently and identically, the HLM allows for both within-state and between-state variances. Therefore, the HLM can correct the distortion from different sample sizes across states and the distortion in standard errors due to within-state clustering [Griffin et al. (2021a)].

When examining the relation between state income inequality and firm innovation, I use two dependent variables: the natural logarithm of the number of patents applied for in a given

year and the natural logarithm of the total forward citations per patent applied for in a given year. These innovation proxies are time- and technology-adjusted.[6]

4.2. Key Variables

4.2.1. Income Inequality

For income inequality data, I use the Frank–Sommeiller–Price Series, which contains a state-level panel of annual income inequality measures based on U.S. Internal Revenue Service (IRS) income tax filing data from 1917 to 2018 [Frank (2009)]. The income inequality measures utilized in the test are the top 10% income share and the Gini coefficient.

For the robustness analysis, I also use the first principal component of the following nine income inequality measures: the top income share (top 10%, 5%, 1%, 0.5%, 0.1%, and 0.01%), average income share from the top 10% to the top 1%, the Gini coefficient, and the Gini coefficient of the bottom 99% of the income distribution. Because the patterns of income inequality measures differ and no pattern reflects the complete status of income inequality, I use the first component of these measures as a proxy for income inequality in this analysis.

4.2.2. Income Deprivation

Given that relative deprivation is derived from one attribute of income inequality, the difference in income inequality with an appropriate comparison group can be used as a proxy for relative deprivation. Considering that the purpose of welfare expenditure is to reduce income inequality, higher income inequality in states with comparable welfare expenditure may lead to employee discouragement due to intrinsic motivation; thus, welfare expenditure-proximate states are regarded as a comparative group. In this study, the comparison group for measuring state-level

[6] Since Compustat reports firms' current headquarters locations, there is a measurement error if the firm relocates to another state due this sample period. However, this could be a minor issue due to the small proportion of relocating firms. Pirinsky and Wang (2006) find only 118 relocating firms out of more than 5,000 firms in their sample.

relative deprivation comprises welfare-proximate states based on welfare expenditure per capita, to identify the five states with the closest match in welfare characteristics.

Among the 50 states and the District of Columbia, the top five states with the smallest differences in welfare expenditure per capita are selected and classified into comparison groups for each state for a given year. Income deprivation is measured as the difference between the mean income inequality measure ($\overline{r_{p,t}}$) of the five welfare-proximate states (p) for a given year (t) and the income inequality measure ($r_{j,t}$) of the state (j) in which each firm is located for a given year (t). State j's income deprivation measure is calculated as follows:

$$Income\ Deprivation_{j,t} = r_{j,t} - \overline{r_{p,t}}. \quad (8)$$

A positive value for the state's income deprivation indicates that the state is relatively deprived of income compared to its welfare-proximate states.[7]

In Figure 3, income inequality and deprivation exhibit similar trends. However, Figure 4 suggests possible differences in the ranking and extent of income inequality and deprivation in states that can change from year to year. For example, although the income inequality levels in Florida and Washington are similar, the sense of income deprivation is much greater in Florida than in Washington (see Figure 5). Based on Bénabou and Tirole's (2006) model, this study examines how income inequality and deprivation contribute to corporate innovation.[8]

[Insert Figures 3, 4, and 5 Here]

4.2.3. Corporate Innovation Measures

[7] Negative income deprivation can be interpreted as a measure of income satisfaction, contrasting the concept of relative deprivation [Yitzhaki (1979)].
[8] Appendix B is included to enhance the clarity and understanding of the measures of income inequality and income deprivation.

Monetary incentives and deprivation can be directly linked to extrinsic and intrinsic motivations, respectively. These motivations can affect the quantity and quality of corporate innovation. Specifically, extrinsic motivation based on monetary incentives can lead to increased quantitative innovation in an attempt to improve income. Simultaneously, intrinsic motivation weakened by deprivation can reduce qualitative innovation. Through these two channels, quantitative and qualitative innovation proxies are required to analyze the impact of the two competing characteristics of income inequality on corporate innovation. Thus, I use two corporate innovation measures: the number of patents granted by a firm in a year and the total number of forward citations per patent granted by a firm in a year. The number of patents granted by a firm is a proxy for measuring innovative output. However, the patent count is limited in terms of its impact on industries related to innovative output. While the patent count merely measures the quantity of innovative output, the total number of citations provides information on the usefulness of innovative output. Based on the characteristics of the two corporate innovation measures, patent counts and citations per patent are interpreted as quantitative and qualitative corporate innovations, respectively.[9] Following Lerner and Seru (2021), I adjust for time and technology biases in both patent counts and citations, considering truncation problems, changes in patent office policy, and technological fluctuations.[10] Additionally, I use the number of citations, excluding self-citations, to capture the innovation quality of each firm and prevent potential spillovers from a given invention by the firm that owns it. Then, I construct a firm-level patent database from 1950 to 2020 based on three patent datasets: Kuhn, Younge, and Marco

[9] Previous studies utilize firms' patenting activities as a proxy for innovation and measure innovation quality using citations [Hall, Jaffe, and Trajtenberg (2001), Fang, Tian, and Tice (2014), Hirshleifer, Hsu, and Li (2018), Shu, Tian, and Zhan (2022)].

[10] To adjust the technology bias, I identify the technology of each patent based on Cooperative Patent Classification (CPC).

(2020), Autor, Dorn, Hanson, Pisano, and Shu (2020), and Kogan, Papanikolaou, Seru, and Stoffman (2017). Patents are counted only if their applications are approved.

CHAPTER 5. EMPIRICAL RESULTS

5.1. Summary Statistics

Table 1 presents summary statistics for the state- and firm-level dependent and key independent variables. For each variable, the 5th percentile, 25th percentile, median, mean, 75th percentile, 95th percentile, standard deviation, and number of observations are reported. The two corporate innovation proxies are highly skewed; therefore, the natural logarithms of these variables are taken. The average log-transformed patent count and number of citations per patent are 0.433 and 0.131, respectively. Income inequality includes the income shares of the top 10%, top 5%, top 1%, top 0.5%, top 0.1%, and top 0.01%; the average income shares from the top 10% to the top 2%; the Gini coefficient; and the Gini coefficient of the bottom 99% of the income distribution. The average income shares of the top 10%, 5%, 1%, 0.5%, 0.1%, and 0.01% are 40.9%, 29.1%, 14.9%, 11.5%, 6.5%, and 2.8%, respectively. The average Gini coefficient and bottom 99% Gini coefficient are 0.564 and 0.488, respectively. Following the literature, sales and scaled property, plant, and equipment (PPE) are log-transformed. The average book leverage is 0.253, Tobin's Q is 2.077, ROA is 0.028, scaled R&D is 0.044, and the log-transformed sales growth is 0.773. The average Lerner index score is 0.165. The sample period is from 1977 to 2018.[11]

[Insert Table 1 Here]

Table 2 presents the correlation matrix between the income inequality measures, income deprivation measures, and the distribution of each measure. The top-income shares (top 10% and 1%, 0.5%, 0.1%, and 0.01%) exhibit significant correlations. Similarly, the broad measures of

[11] All financial and accounting data are obtained from Compustat. Following the innovation literature, I control for firm-level characteristics. To minimize the impact of extreme values on the regression, I winsorize all firm-level variables at the 1% and 99% levels.

income inequality (the Gini coefficient and bottom 99% Gini) also demonstrate strong correlations. However, when comparing these distinct measures, the correlations between the top income shares and broad income inequality measures tend to be relatively low. Meanwhile, the average income shares from the top 10% to the top 1% have low correlations with the top income shares and the broad income inequality measures. Additionally, Table 2 reports the correlations between income deprivations and all other income inequality measures. The top income shares are highly correlated with each other, ranging from 0.831 to 0.995. The Gini coefficients are also highly correlated with each other, at 0.909. However, the correlations between the top income shares and the Gini coefficients range from 0.359 to 0.780. The average top income share has a relatively low correlation with any other top income shares and the Gini coefficients, ranging from 0.191 to 0.663. The correlations between income inequality measures and income deprivations range from -0.062 to 0.710, indicating that, while income deprivations are mostly positively related to income inequality measures, none exhibit a high correlation. These results suggest that a sense of deprivation does not arise simply because income inequality is high.

[Insert Table 2 Here]

5.2. Regression Results

Table 3 reports the HLM regression results of corporate innovation on income inequality. Due to the limited availability of high-quality, sufficient data on firm-level income inequality, I leverage state-level income inequality measures spanning a century. These capture various aspects of annual income distribution within each state. This research investigates how state income inequality influences corporate innovation. While prior studies have primarily focused on correlations between income inequality and national, state, or administrative-level variables,

none have explored the impact of state income inequality on firm-level innovation.[12] To address this gap, I utilize a two-level HLM. This approach mitigates biases arising from state-level sample size variations and addresses standard error issues by clustering observations within states.

Panel A of Table 3 shows that state income inequality is positively related to quantitative innovation at the firm level. Columns (1)-(4) report the full HLM regression results on top 10% income share. Columns (5)-(6) present the HLM regression results on the Gini coefficients; the relation between state-level income inequality and quantitative innovation remains significantly positive in columns (1)-(6). However, the regression results in Panel B of Table 3 indicate that state income inequality is no longer significantly correlated with qualitative corporate innovation. This finding confirms Aghion et al.'s (2018) findings that innovation has a positive and significant relation with top income shares, but an insignificant or negative relation with broad income inequality measures.

In addition, these results support the existence of extrinsic motivation, suggesting that overall income inequality acts as a monetary incentive to stimulate quantitative innovation. My theoretical framework also supports the positive relation between monetary incentives and quantitative innovation because monetary incentives linked to extrinsic motivation are linearly related to corporate innovation. The state-level population does not have a significant implication for qualitative innovation but shows a significantly negative relation with quantitative innovation. The state-level collectivism index has a significant and negative relation with qualitative innovation. The coefficient estimate of collectivism indicates that firms in

[12] Prior literature [Jurio and Yook (2012), Chen, Podolski, Rhee, and Veeraraghavan (2014), Chino (2016), Serfling (2016), Li, Griffin, Yue, and Zhao (2011), Duong, Nguyen, Nguten, and Rhee (2020), Griffin, Li, and Xu (2021a)] shows that firm-level activities can be significantly affected by factors, such as laws, economic conditions, culture, and the upper-level environment (county, state, or country) where the firm is located.

individualistic states engage in more innovation, supporting Chui, Titman, and Wei (2010) and Chen, Dou, Rhee, Truong, and Veeraraghavan (2015)[13].

Furthermore, similar to the findings of Chen et al. (2014) and Fang et al. (2014), I find that firm-level within-state variables have similar implications for both types of corporate innovation. While sales, scaled PPE, Tobin's Q, and scaled R&D expenditure have positive and significant relations with both quantitative and qualitative innovations at the firm level, book leverage and the Lerner index have negative and significant relations with both types of innovation. ROA and sales growth have different relations with quantitative and qualitative innovation. The coefficient estimates for ROA and sales growth are negative for quantitative innovation, but positive and significant for qualitative innovation. As firm-level characteristics within and across states are decomposed, firm-level cross-state effects on firm-level innovation can differ from firm-level within-state effects. For example, quantitative innovation has a negative relation with scaled PPE and Tobin's Q in columns (2) and (4) of Panel A, while qualitative innovation has a negative relation with ROA but a positive relation with the Lerner index in columns (2) and (4) of Panel B.

[Insert Table 3 Here]

Table 4 presents regression results concerning the relation between income deprivation and corporate innovation. Four income deprivation proxies are derived based on top 10% and 1% income shares and two Gini coefficients. Panel A shows the regression results of corporate

[13] They find that firms in individualistic regions engage in more innovation. I use state-level collectivism index developed by Vandello and Cohen (1999). After controlling for the local culture variable, I still find the consistent relation of the main findings: the positive relation between income inequality and quantitative innovation and the negative relation between income deprivation and qualitative innovation. Specifically, when the Gini coefficient increases one standard deviation, it relates to an increase in log-transformed patent count by 0.016. When the deprivation increases one standard deviation, it relates to a decrease in log-transformed citation per patent by 0.002. When the collectivism variable increases one standard deviation, it relates to a decrease in log-transformed patent count by 0.021 and a decrease in log-transformed citation per patent by 0.009.

quantitative innovation on state-level income deprivation. Columns (1)–(4) show that state income deprivation based on the top 10% income share has a positive and significant relation to corporate quantitative innovation. Columns (5)-(6) also show a significant relation with income deprivation based on the Gini Coefficient. However, Panel B shows that state income deprivation is either insignificantly or significantly negatively related to corporate qualitative innovation, depending on the base income inequality measures. This result supports the existence of intrinsic motivation and implies that deprivation may hinder innovation quality. Furthermore, this finding aligns with relative deprivation theory, which suggests that income inequality may weaken employees' intrinsic motivation and thus undermine qualitative innovation. In summary, the results indicate that the effects of firm-and other state-level variables on corporate innovation have consistent implications.

[Insert Table 4 Here]

In addition, I test whether a significant deviation in income inequality across states weakens corporate innovation. Because a high degree of income deprivation results in substantial variations in income inequality, I test the effects of relative deprivation on corporate innovation. Table 5 presents the regression results for the relation between corporate innovation outputs and the standard deviation of income inequality measures across states. The results suggest that a large deviation in income inequality among states contributes to a decrease in corporate innovation. Although income inequality can help reinforce quantitative innovation as a monetary incentive, the widening gap in regional income inequality measures within a country can impair corporate innovation quantity and quality. Therefore, the result also suggests the existence of relative deprivation.[14]

[14] I use composite measures of relative deprivation to test their impact on corporate innovation. The regional deprivation indices are the social deprivation index (SDI) and the area deprivation index (ADI) (see Appendix C).

Overall, the results in Tables 4 and 5 exhibit a form of deprivation that may weaken intrinsic motivations but significantly affect the byproducts of intrinsic motivation, namely, qualitative innovation. Additionally, qualitative innovation is more active in states with larger populations or expresses more assertive individualism. These results suggest that the federal government may need to focus more on narrowing the income inequality gap among welfare-proximate states to mitigate the negative impact of deprivation, ultimately leading to a positive effect on corporate innovation.

[Insert Table 5 Here]

Table 6 shows the analysis results regarding the relation between corporate innovation and the contributor groups derived from the model in Chapter 3. Considering that contributors actively engage in corporate innovation as a prosocial behavior, states belonging to the contributor group are expected to be more innovative in a given year. Figure 6 shows the distribution of income inequality and income deprivation based on state-year data in the United States. A segmented regression curve is used as the boundary condition for the model in Chapter 3.[15] Contributors are distinguished from non-contributors based on the approximate boundary conditions. As expected, the results show that the contributor group experience an increase in corporate innovation.

[Insert Table 6 and Figure 6 Here]

These deprivation indices represent a wide range of deprivation levels, including not only income but also food, physical, and mental distress in each region. The composite measures of regional deprivation have a negative relation with corporate innovations in both quantity and quality. This suggests that relative deprivation negatively impacts corporate innovations, even when it is not limited to income.

[15] I use the piecewise linear regression model. Below the curve are contributors, and above the curve are non-contributors. Additionally, I utilize other approximations near the curve, and the results align with those presented in Table 6.

Finally, I test whether industry innovativeness affects the relation between corporate innovation and the two income inequality characteristics. Following Hirshleifer, Low, and Teoh (2012), I use the two-digit SIC. An industry is considered innovative if the time- and technology-adjusted citation count per patent of the sector is greater than the median adjusted citation count per patent across all industries in a given year; otherwise, it is regarded as non-innovative. The HLM regression results in Table 7 show that in innovative industries, income inequality and corporate innovation quantity have a positive relation, whereas deprivation and corporate innovation quality have a negative relation. These results are consistent with the main regression results presented in Tables 3 and 4. Interestingly, income inequality and deprivation are positively correlated with quantitative innovation in non-innovative industries. This can be interpreted as an extrinsic motivation, which is directly dependent on monetary incentives and heavily influences short-term innovation performance in non-innovative industries.

[Insert Table 7 Here]

CHAPTER 6. ROBUSTNESS TESTS

6.1. General Robustness Tests

6.1.1. Exclusion of Self-citation

To assess the robustness of the main findings, I repeat the HLM regressions in Chapter 5, but exclude self-citations.[16] I find that the relation between income inequality measures and corporate innovation remains largely unchanged. Rows (1a) and (1b) of Table 8 present the regression results, which are consistent with those in Tables 3 and 4.

6.1.2. First Component of Income Inequality Measures

As stated in Chapter 2, each income inequality measure has strengths and weaknesses. Moreover, the correlation between income inequality measures varies depending on the time or region. As shown by Aghion et al. (2018), demonstrating a significant and consistent correlation between a particular variable and all income inequality measures can be challenging. Therefore, I use the first principal component of the nine income inequality measures as a proxy for income inequality to capture common characteristics in a single variable. All states' historical income inequality measures are pooled to derive a parsimonious index:

$$Income\ Inequality_{jt} = 0.3660Top10_{jt} + 0.3725Top5_{jt} + 0.3713Top1_{jt} + \quad (9)$$
$$0.3708Top0.5_{jt} + 0.3642Top0.1_{jt} + 0.3499Top0.01_{jt} + 0.1837AvgTop_{jt} +$$
$$0.3316Gini_{jt} + 0.2304Gini99_{jt}\ ,$$

where each index component is standardized to have a zero mean. The regression results in row (2) of Table 8 are consistent with those in Table 3.

6.1.3. Income Inequality without Standardization

[16] Gomes-Casseres, Hagedoorn, and Jaffe (2006) show that inter-firm alliances increase the number of self-citations. Balsmeier, Fleming, and Manso (2017) find that fewer self-citations imply the expansion of the firm's innovative efforts.

I investigate whether a change in the methodology for calculating the first principal component of the income inequality measures significantly affects the results. I utilize the first component of income inequality measures centered around zero without standardization. While standardization is commonly employed in principal component analysis, I consider several factors that may not necessitate standardization in the context of my study. In this study, the income inequality component measures are expressed as decimal numbers ranging from zero to one. Because they are defined on the same scale (with a lower bound of zero and an upper bound of one), a substantial deviation in each variable can provide valuable information regarding income inequality. Normalization may restrict this feature [James, Witten, Hastie, Tibshirani (2013), Nguyen and Holmes (2019)]. Unlike the broad income inequality measures, which exhibit a roughly normal distribution, the distribution of the top-income shares is skewed to the right (see Table 2). Thus, higher shares of upper income result in higher distribution skewness. Considering the importance of information on top income shares within the income inequality measure, normalization could lead to a loss of such information. To address this concern, I perform HLM regressions, and the results are presented in row (3) of Table 8. The results support the main findings.

6.1.4. Income Inequality Based on Maximum Data

The income inequality component measures are annual indices, and a longer data period tends to yield more consistent factor loadings, as obtained through the principal component analysis. Therefore, I investigate whether utilizing the full range of time-series data for income inequality components in constructing the first component affects the results. Rows (4) and (5) of Table 8 present the regression results, which show that the first component based on the maximum time-series data remain similar to that primarily used in this study.

6.1.5. Controlling for Tax Burden

Taxes play a crucial role in influencing corporate decision-making. Particularly, state and local taxes can significantly affect a firm's capital structure, debt financing, distribution, and location [Miller (1977), Buss (2001), Hennessy and Whited (2005), Graham and Tucker (2006), Wang, Xu, and Sun, and Cullinan (2020)]. Furthermore, high-powered incentives can influence corporate tax avoidance strategies [Desai and Dharmapala (2006)]. Similarly, the state's tax burden may provide a different perspective on how employee motivational status affects corporate innovation. Thus, I control for the tax burden rate. Row (6) of Table 8 presents the test results. The results show that state tax burden rate has a positive effect on innovation quantity; although, it weakens innovation quality. This suggests that, while the tax burden may stimulate quantitative outcomes through monetary incentives, it may also diminish the overall quality of those outcomes. Subsequently, I include the state tax burden rate, and the test results are presented in rows (6a)-(6c) of Table 8. Row (6a) of Table 8 presents an insignificant relation between the Gini coefficient and quantitative innovation after controlling for tax burden, but I find a positive and significant relation with quantitative innovation from the first component of income inequality measures in row (6b) of Table 8. In addition, the results in row (6c) of Table 8 show that income deprivation is negatively correlated with innovation quality. The overall results are consistent with the main findings presented in Tables 3 and 4.

6.1.6. Exclusion of Income Satisfaction

For the empirical analysis in Chapter 5, negative income deprivation is also considered as a measure of relative satisfaction [Yitzhaki (1979)]. However, the theoretical framework in Chapter 3 does not account for relative satisfaction. To align the two relative deprivation measures, I examine the relation between positive income deprivation and corporate innovation

outcomes. Row (7a) of Table shows income deprivation, using the Gini coefficient, does not have a negative and significant relation with qualitative innovation. However, Row (7b) of Table 8 presents the regression results on another Gini coefficient (Gini99), which are consistent with the findings in Chapter 5.

6.1.7. Consideration of Time Truncation

Although patent data are available, time truncation is a concern due to the difference between filed and granted patents [Hall, Jaffe, and Trajtenberg (2005), He and Tian (2013), Chen et al. (2014), Fang et al. (2014)]. Hall et al. (2001) find that 85% and 95% of filed patents are granted within two and three years, respectively. Because my patent data are collected before 2020 and my findings in Chapter 5 are based on patent data up to 2018, I utilize patent data up to 2017 for this test. The results presented in Row (8) of Table 8 remain consistent with the original findings.

6.1.8. Exclusion of Zero Patent Observations

Rows (9a) and (9b) of Table 8 show the test results when firm-year observations with zero patents are excluded. The results indicate that there is a positive relation between innovation quantity and income inequality, and a negative relation between innovation quality and deprivation. Income inequality remains positive in the regressions of patent counts but exhibits a negative and significant relation with total citations per patent. Income deprivation is still significantly negatively related to qualitative innovation. This finding suggests that deprivation overrides the monetary incentives inherent in income inequality. Specifically, when the sample is limited to firms with more than one patent, the monetary incentives of income inequality decrease.

6.1.9. Variation in Lag Structure

I conduct robustness tests using various lag structures to ensure the stability of the results over different time horizons. Rows (10a)-(10f) of Table 8 show the test results confirm that the main findings remain consistent across different lag specifications. I find that the consistent relation with the main findings holds up to three lags. This is understandable because 95% of patent applications are eventually granted within three years [Hall et al. (2001)]. If monetary incentives and relative deprivation affect corporate innovation, up to three-year lags may justify the consistent relation. Beyond the three-year lags, potential confounding factors may influence the relation between income inequality and corporate innovation.

6.1.10. History Bias in Patent Citations

I perform robustness tests to account for history bias by limiting patent citations up to five years after their application. Following Aghion et al. (2018), this approach could reduce the potential history bias, where older patents tend to have more citations than newer patents, despite having equivalent innovation. I recount the total citations for each patent up to five years after its application and aggregated them at the firm level. The recomputed patent citation data are available up to 2017. To ensure that the latter patents can accumulate citations for a full five years, I use data up to 2012. In Rows (11a) and (11b) of Table 8, the test results are consistent with the main findings: qualitative innovation has an insignificant relation with income inequality but a significant and negative relation with income deprivation. This confirms that the main findings are not driven by the age of the patents.

[Insert Table 8 Here]

6.2. Endogeneity Issues

In this study, income inequality exhibits a positive relation with innovation quantity, but income deprivation shows a negative relation with innovation quality. Despite all independent variables

being lagged by one year, establishing two causal relations: (i) monetary incentive and quantitative innovation; and (ii) income deprivation and qualitative innovation remain necessary to address potential omitted variable bias or reverse causality concerns. Thus, I employ a two-stage least squares (2SLS) model using extreme temperature as an IV for income inequality [Miguel et al. (2004)]. As an exogenous weather shock, extreme temperatures can result in an overall economic slowdown that has a greater effect on low-income groups. For example, Marx (2018) shows the negative marginal effects of extreme temperatures on the lowest-income decile. Additionally, several studies indicate that the severe impacts of climate change have adverse effects on income. Dell, Jones, and Olken (2009) find a negative cross-sectional relation between temperature and income within and across the Americas. Moreover, Diffenbaugh and Burke (2019) and Dasgupta, Emmerling, and Shayegh (2020) demonstrate that global warming increases income inequality.

A valid IV is required to meet both the relevance and exogeneity conditions. First, the relevance condition must be satisfied based on direct evidence. For the IV test, extreme temperature is a dummy variable that takes the value of one if each state's heating degree days (HDD) or cooling degree days (CDD) exceed one standard deviation of HDD or CDD, and zero otherwise. The degree days data cover the period from 1895 to 2017 but do not include Alaska, Hawaii, and the District of Columbia.[17] Second, satisfying the exclusion restriction poses a greater challenge, as determining whether temperatures solely influence innovation through inequality is difficult. To mitigate the potential confounding effects of extreme weather shocks on corporate innovation, patents pertaining to agriculture or food are excluded from the analysis. This strategic exclusion is essential because of the intricate relation between weather shocks and

[17] I collect state-level temperature data from the U.S. Climate Divisional Database.

the invention of patents in these sectors as well as their subsequent citations. Extreme weather events, particularly those affecting agricultural production, can directly affect the development and citation of patents related to agriculture and food. Column (1) of Table 9 presents the first-stage regression results, which indicate a positive relation between the extreme temperature variable and state income inequality. Column (2) of Table 9 demonstrates that the positive relation between income inequality and corporate innovation remains significant.

[Insert Table 9 Here]

To establish a causal relation between deprivation and qualitative innovation, a two-stage channel analysis is conducted following Liang and Renneboog (2017) and Griffin, Guedhami, Li, and Lu (2021b). Deprivation can lead to political uncertainty, which decreases corporate innovation. Previous studies [Majeed (1979), Julio and Yook (2012), Bhattachartya, Hsu, Tian, and Xu (2017), Korotayev and Shishkina (2020)] suggest that political uncertainty links the sense of deprivation to corporate innovation. In this study, I consider three political uncertainty channels and one policy uncertainty channel that connect a state's income deprivation to corporate innovation.

I examine whether political channels link state-level income deprivation to firm-level innovation. Following Jurio and Yook (2012) and Çolak, Durnev, and Qian (2017), I utilize U.S. gubernatorial election results and define politically uncertain election years based on three criteria: winning margin, governor change, and absence of an incumbent. Based on the winning margin criterion, I sort all elections by the vote difference between the winner and runner-up, and designate the bottom tercile as a period of high political uncertainty. The second criterion is a governor change occurring with a winning margin of less than 5%. If an election satisfies this criterion, it is considered a period of high political uncertainty. The third criterion is the absence

of an incumbent governor, excluding term limit issues, which indicates a period of heightened political uncertainty. In the first stage, I regress state-level political channel variables on a state-level income deprivation dummy variable for the election year.[18] In the second stage, I regress firm-level innovation (patent citations for Panel A of Table 10) on the state-level channel variables predicted by the first-stage regressions using the state-level income deprivation measure. I include all firm characteristics in the analysis. Columns (1), (3), (5), and (7) in Panel A of Table 10 represent the first-stage analysis, whereas columns (2), (4), (6), and (8) in Panel A of Table 10 represent the second-stage analysis. The results demonstrate that through political uncertainty channels, a state's income deprivation can weaken corporate innovation. Specifically, income deprivation may exacerbate political uncertainty through the winner margin and absence of incumbent channels, thereby weakening corporate qualitative innovation. As Majeed (1979) and Korotayev and Shishkina (2020) show, political instability tends to arise from relative deprivation.

In addition to political uncertainty channels, I further investigate whether policy risk affects the relation between income deprivation and corporate innovation. State-level policy uncertainty can arise from a state's political alignment with the president's party [Kim, Pantzalis, and Park (2012), Kim and Park (2021)]. I find that income deprivation in a state can lead to political misalignment with the president's party, indicating that deprivation caused by income inequality can oppose the current federal government's policies.

Overall, the channel analysis is similar to IV regression, but with corporate innovation being explained through channels predicted by the state's income deprivation in the first stage. Following the IV approach, I still consider the exclusion restriction, though there is a caveat:

[18] Income deprivation dummy takes the value of one if the state's income deprivation for a given year is greater than zero, and zero otherwise.

relative deprivation with local government might directly affect employees' work quality. To mitigate concerns about instrument exogeneity, I conduct overidentification tests to assess the validity of the IVs. Specifically, I use income deprivation dummies from four different income inequality measures as IVs and perform Sargan and Basmann tests for the channels. In Panel B of Table 10, the results of these tests suggest that the instruments are valid for our analysis. In summary, the findings in Table 10 indicate that income deprivation tends to increase election and policy uncertainty, thereby reducing qualitative innovation.

[Insert Table 10 Here]

CHAPTER 7. CONCLUSIONS

This study provides evidence that the dual aspects of income inequality significantly influence corporate innovation. Building on Bénabou and Tirole's (2006) theoretical framework, this study introduces a psychological factor (relative deprivation) and constructs a model in which monetary incentives and relative deprivation, which are associated with extrinsic and intrinsic motivation, shape innovation outcomes. This study shows that: (i) monetary incentives, which are linked to extrinsic motivation, encourage quantitative innovation; (ii) income deprivation, which is tied to intrinsic motivation, undermines qualitative innovation; and (iii) even when income deprivation remains at a low level, monetary incentives support both qualitative and quantitative innovations.

The IV regression is employed to analyze monetary incentives while a two-stage channel analysis is adopted to investigate income deprivation. In-state extreme weather shocks exacerbate state income inequality, which stimulates monetary success and compensation. This subsequently fosters a surge in innovation volume. Conversely, income deprivation amplifies political uncertainty, which represents apathy and dissatisfaction. This results in weakened innovation quality.

Taken together, this study contributes to the current literature on the importance of income inequality in corporate performance. I present the first empirical evidence on the dual characteristics of income inequality in relation to corporate innovation. While monetary incentives associated with income inequality enhance innovation quantity, income deprivation resulting from such inequality undermines innovation quality. Given that income deprivation arises from comparisons with other states with similar welfare conditions but lower income inequality, these findings highlight the potential of policies aimed at alleviating relative

deprivation to spur both quantitative and qualitative corporate innovation. Specifically, the findings suggest that interventions aimed at narrowing the income gap among states with similar industrial profiles are more effective in promoting innovation than initiatives focused solely on reducing income disparities within individual states.

TABLE 1
Summary Statistics

Table 1 presents the summary statistics of key variables. All dependent variables are adjusted for time and technology bias. Income inequality is represented by the first principal component of nine income inequality measures, which have been standardized. The nine income inequality measures consist of the income shares of the top 10%, top 5%, top 1%, top 0.5%, top 0.1%, and top 0.01%; the average income shares from the top 10% to the top 2%; the Gini coefficient; and the Gini coefficient of the bottom 99% of the income distribution. Income deprivation measures are based on state welfare spending per capita. The full sample period spans from 1977 to 2018.

	5%	25%	Median	Mean	75%	95%	Std.Dev	No.Obs.
Dependent Variables								
ln (1 + Patent Count)	0.000	0.000	0.000	0.433	0.000	2.809	1.040	178,337
ln (1 + Citation/Patent)	0.000	0.000	0.000	0.131	0.000	0.842	0.322	178,337
State-level Explanatory Variables								
Top 10%	0.322	0.365	0.404	0.409	0.444	0.511	0.060	2,011
Top 5%	0.210	0.250	0.289	0.291	0.321	0.402	0.058	2,011
Top 1%	0.086	0.116	0.143	0.149	0.169	0.246	0.048	2,011
Top 0.5%	0.059	0.086	0.108	0.115	0.133	0.200	0.043	2,011
Top 0.1%	0.026	0.043	0.058	0.065	0.077	0.129	0.032	2,011
Top 0.01%	0.008	0.017	0.024	0.028	0.034	0.067	0.019	2,011
AvgTop	0.025	0.027	0.029	0.029	0.030	0.034	0.003	2,011
Gini	0.473	0.532	0.567	0.564	0.597	0.647	0.053	2,011
Gini 99	0.415	0.462	0.492	0.488	0.517	0.557	0.043	2,011
RD (Top 10%)	-0.060	-0.026	-0.001	0.003	0.025	0.079	0.043	2,011
RD (Top 1%)	-0.047	-0.019	-0.003	0.002	0.012	0.080	0.037	2,011
RD (Gini)	-0.044	-0.020	-0.004	-0.001	0.015	0.057	0.030	2,011
RD (Gini 99)	-0.044	-0.018	-0.004	-0.002	0.012	0.048	0.029	2,011
Firm-level Explanatory Variables								
ln (Sales)	0.999	3.193	4.765	4.829	6.434	8.735	2.286	178,337
ln (PPE / EMP)	1.458	2.567	3.336	3.520	4.227	6.454	1.482	178,337
Book Leverage	0.000	0.049	0.198	0.253	0.371	0.709	0.261	178,337
Tobin Q	0.776	1.021	1.318	2.077	2.104	5.798	2.304	178,337
ROA	-0.456	0.017	0.094	0.028	0.159	0.274	0.308	178,337
R&D / Assets	0.000	0.000	0.000	0.044	0.035	0.233	0.104	178,337
Sales Growth	0.514	0.682	0.737	0.773	0.810	1.130	0.230	178,337
Lerner Index	-0.177	0.191	0.315	0.165	0.468	0.759	1.210	178,337

TABLE 2
Correlation between Income Inequality Measures

Table 2 presents the correlation matrix for income inequality measures, income deprivation measures, and the distribution of each measure. The following income inequality measures are used: the income shares of the top 10%, top 5%, top 1%, top 0.5%, top 0.1%, and top 0.01%; the average income shares from the top 10% to the top 2%; the Gini coefficient; and the Gini coefficient of the bottom 99% of the income distribution. Income deprivation measures are based on state welfare spending per capita. The full sample period spans from 1977 to 2018.

TABLE 3
Income Inequality and Corporate Innovation

Table 3 presents the HLM regression results on the relation between state income inequality and corporate innovation outputs. In Panel A, the dependent variable is the natural logarithm of the number of patents applied for in a given year. In Panel B, the dependent variable is the natural logarithm of the total citations per patent applied for in a given year. All dependent variables are adjusted for time and technology bias, and all independent variables are lagged by one year. The inclusion of year and 2-digit SIC industry fixed effects is indicated at the bottom of each model. Standard errors are presented in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Panel A. Income Inequality and Quantitative Innovation

	ln (1 + Patent Count)			
	(1)	(2)	(3)	(4)
	Within-State	Cross-State	Within-State	Cross-State
State Characteristics				
Top 10%		0.311***		0.354***
		(0.106)		(0.106)
ln (Population)				-0.032**
				(0.016)
Collectivism				-0.217
				(0.162)
Firm Characteristics				
ln (Sales)	0.220***	0.153***	0.220***	0.154***
	(0.001)	(0.010)	(0.001)	(0.011)
ln (PPE / EMP)	0.064***	-0.029**	0.064***	-0.030**
	(0.002)	(0.012)	(0.002)	(0.013)
Book Leverage	-0.304***	-0.445***	-0.302***	-0.462***
	(0.009)	(0.079)	(0.009)	(0.080)
Tobin Q	0.042***	-0.020**	0.041***	-0.023**
	(0.001)	(0.009)	(0.001)	(0.009)
ROA	-0.012	-0.314***	-0.013	-0.366***
	(0.010)	(0.095)	(0.010)	(0.097)
R&D / Assets	0.978***	3.297***	0.973***	3.263***
	(0.027)	(0.217)	(0.027)	(0.219)
Sales Growth	-0.037***	0.037	-0.037***	0.026
	(0.009)	(0.080)	(0.009)	(0.081)
Lerner Index	-0.017***	-0.024	-0.017***	-0.021
	(0.002)	(0.019)	(0.002)	(0.019)
Year FEs		Yes		Yes
Industry FEs		Yes		Yes
Observations		178,337		177,871

	ln (1 + Patent Count)	
	(5)	(6)
	Cross-State	Cross-State
Gini	0.315**	0.311***
	(0.140)	(0.139)
All state characteristics	No	Yes
Year FEs	Yes	Yes
Industry FEs	Yes	Yes
Observations	178,337	177,871

TABLE 3 (Continued)
Income Inequality and Corporate Innovation

Panel B. Income Inequality and Qualitative Innovation

	ln (1 + Citation per Patent)			
	(1)	(2)	(3)	(4)
	Within-State	Cross-State	Within-State	Cross-State
State Characteristics				
Top 10%		0.070**		0.075**
		(0.034)		(0.034)
ln (Population)				0.006
				(0.004)
Collectivism				-0.090**
				(0.037)
Firm Characteristics				
ln (Sales)	0.043***	0.036***	0.043***	0.035***
	(0.000)	(0.003)	(0.000)	(0.003)
ln (PPE / EMP)	0.016***	0.016***	0.016***	0.017***
	(0.001)	(0.004)	(0.001)	(0.004)
Book Leverage	-0.104***	-0.220***	-0.104***	-0.216***
	(0.003)	(0.025)	(0.003)	(0.026)
Tobin Q	0.014***	-0.001	0.014***	-0.003
	(0.000)	(0.003)	(0.000)	(0.003)
ROA	0.032***	-0.103***	0.032***	-0.100***
	(0.003)	(0.031)	(0.003)	(0.031)
R&D / Assets	0.308***	0.670***	0.308***	0.686***
	(0.009)	(0.069)	(0.009)	(0.070)
Sales Growth	0.023***	0.003	0.023***	0.001
	(0.003)	(0.026)	(0.003)	(0.026)
Lerner Index	-0.004***	0.022***	-0.004***	0.023***
	(0.001)	(0.006)	(0.001)	(0.006)
Year FEs		Yes		Yes
Industry FEs		Yes		Yes
Observations		178,337		171,442

	ln (1 + Citation per Patent)	
	(5)	(6)
	Cross-State	Cross-State
Gini	-0.023	-0.017
	(0.045)	(0.045)
All state characteristics	No	Yes
Year FEs	Yes	Yes
Industry FEs	Yes	Yes
Observations	178,337	177,871

TABLE 4
Income Deprivation and Corporate Innovation

Table 4 presents the HLM regression results on the relation between state income deprivation and corporate innovation outputs. In Panel A, the dependent variable is the natural logarithm of the number of patents applied for in a given year. In Panel B, the dependent variable is the natural logarithm of the total citations per patent applied for in a given year. All dependent variables are adjusted for time and technology bias, and all independent variables are lagged by one year. The inclusion of year and 2-digit SIC industry fixed effects is indicated at the bottom of each model. Standard errors are presented in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Panel A. Income Deprivation and Quantitative Innovation

	ln (1 + Patent Count)			
	(1)	(2)	(3)	(4)
	Within-State	Cross-State	Within-State	Cross-State
State Characteristics				
RD (Top 10%)		0.257***		0.277***
		(0.084)		(0.084)
ln (Population)				-0.029*
				(0.016)
Collectivism				-0.222
				(0.163)
Firm Characteristics				
ln (Sales)	0.220***	0.154***	0.220***	0.156***
	(0.001)	(0.010)	(0.001)	(0.011)
ln (PPE / EMP)	0.064***	-0.029**	0.064***	-0.029**
	(0.002)	(0.012)	(0.002)	(0.013)
Book Leverage	-0.304***	-0.448***	-0.302***	-0.466***
	(0.009)	(0.079)	(0.009)	(0.079)
Tobin Q	0.042***	-0.019**	0.041***	-0.021**
	(0.001)	(0.009)	(0.001)	(0.009)
ROA	-0.012	-0.320***	-0.013	-0.371***
	(0.010)	(0.095)	(0.010)	(0.097)
R&D / Assets	0.978***	3.300***	0.973***	3.269***
	(0.027)	(0.217)	(0.027)	(0.219)
Sales Growth	-0.037***	0.046	-0.037***	0.038
	(0.009)	(0.080)	(0.009)	(0.081)
Lerner Index	-0.017***	-0.024	-0.017***	-0.021
	(0.002)	(0.019)	(0.002)	(0.019)
Year FEs		Yes		Yes
Industry FEs		Yes		Yes
Observations		178,309		177,871

	ln (1 + Patent Count)	
	(5)	(6)
	Cross-State	Cross-State
RD (Gini)	0.436***	0.420***
	(0.105)	(0.105)
All state characteristics	No	Yes
Year FEs	Yes	Yes
Industry FEs	Yes	Yes
Observations	178,309	177,871

TABLE 4 (Continued)
Income Deprivation and Corporate Innovation

Panel B. Income Deprivation and Qualitative Innovation

	ln (1 + Citation per Patent)			
	(1)	(2)	(3)	(4)
	Within-State	Cross-State	Within-State	Cross-State
State Characteristics				
RD (Top 10%)		0.012		0.018
		(0.027)		(0.028)
ln (Population)				0.007*
				(0.004)
Collectivism				-0.090**
				(0.038)
Firm Characteristics				
ln (Sales)	0.043***	0.037***	0.043***	0.036***
	(0.000)	(0.003)	(0.000)	(0.003)
ln (PPE / EMP)	0.016***	0.015***	0.016***	0.017***
	(0.001)	(0.004)	(0.001)	(0.004)
Book Leverage	-0.104***	-0.221***	-0.104***	-0.217***
	(0.003)	(0.025)	(0.003)	(0.026)
Tobin Q	0.014***	-0.000	0.014***	-0.002
	(0.000)	(0.003)	(0.000)	(0.003)
ROA	0.032***	-0.108***	0.032***	-0.104***
	(0.003)	(0.031)	(0.003)	(0.031)
R&D / Assets	0.309***	0.672***	0.308***	0.688***
	(0.009)	(0.069)	(0.009)	(0.071)
Sales Growth	0.023***	0.009	0.023***	0.006
	(0.003)	(0.026)	(0.003)	(0.026)
Lerner Index	-0.004***	0.021***	-0.004***	0.022***
	(0.001)	(0.006)	(0.001)	(0.006)
Year FEs		Yes		Yes
Industry FEs		Yes		Yes
Observations		178,309		177,871

	ln (1 + Citation per Patent)	
	(5)	(6)
	Cross-State	Cross-State
RD (Gini)	-0.084**	-0.076**
	(0.034)	(0.034)
All state characteristics	No	Yes
Year FEs	Yes	Yes
Industry FEs	Yes	Yes
Observations	178,309	177,871

TABLE 5
Relative Deprivation and Corporate Innovation

Table 5 presents the HLM regression results examining the relation between corporate innovation outputs and the standard deviation of Income Inequality for a specific year. Income inequality is based on the state-level Gini coefficient. Columns (1)-(2) report the dependent variable as the natural logarithm of the number of patents applied in a given year. Columns (3)-(4) use the natural logarithm of the total citations per patent applied for in a given year as the dependent variable. All dependent variables are adjusted for time and technology bias, and all independent variables are lagged by one year. The inclusion of year and 2-digit SIC industry fixed effects is indicated at the bottom of each model. Standard errors are presented in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

	ln (1 + Patent Count)		ln (1 + Citation per Patent)	
	(1)	(2)	(3)	(4)
SD (Income Inequality)	-37.000***	-36.547***	-20.807***	-20.952***
	(3.112)	(3.146)	(1.000)	(1.015)
All state characteristics	No	Yes	No	Yes
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	178,337	177,871	178,337	177,871

TABLE 6
Contributor Group and Corporate Innovation

Table 6 presents the HLM regression results examining the relation between corporate innovation outputs and the contributor group identified in Chapter 3. A contributor is assigned a value of one if the state's position on income inequality and relative deprivation space falls within the shaded area of Figure 2(b) for a particular year; otherwise, it is assigned a value of zero. Income inequality and income deprivation are based on the state-level Gini coefficient. In columns (1)-(4), the dependent variable is the natural logarithm of the number of patents filed in a given year. In columns (5)-(8), the dependent variable is the natural logarithm of the total citations per patent filed in a given year. All dependent variables are adjusted for time and technology bias, and all independent variables are lagged by one year. The inclusion of year and 2-digit SIC industry fixed effects is indicated at the bottom of each model. Standard errors are presented in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

	ln (1 + Patent Count)				ln (1 + Citation per Patent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Within-State	Cross-State	Within-State	Cross-State	Within-State	Cross-State	Within-State	Cross-State
State Characteristics								
Contributor		0.013**		0.015**		0.005***		0.005***
		(0.006)		(0.006)		(0.002)		(0.002)
ln (Population)				-0.028*				0.005
				(0.016)				(0.004)
Collectivism				-0.201				-0.083**
				(0.163)				(0.037)
Firm Characteristics								
ln (Sales)	0.219***	0.151***	0.219***	0.152***	0.044***	0.036***	0.044***	0.036***
	(0.001)	(0.011)	(0.001)	(0.011)	(0.000)	(0.003)	(0.000)	(0.003)
ln (PPE / EMP)	0.064***	-0.029**	0.064***	-0.031**	0.017***	0.015***	0.017***	0.016***
	(0.002)	(0.013)	(0.002)	(0.013)	(0.001)	(0.004)	(0.001)	(0.004)
Book Leverage	-0.303***	-0.466***	-0.301***	-0.479***	-0.106***	-0.197***	-0.106***	-0.193***
	(0.009)	(0.081)	(0.009)	(0.081)	(0.003)	(0.026)	(0.003)	(0.027)
Tobin Q	0.040***	-0.026***	0.040***	-0.028***	0.015***	-0.002	0.015***	-0.003
	(0.001)	(0.009)	(0.001)	(0.009)	(0.000)	(0.003)	(0.000)	(0.003)
ROA	-0.020**	-0.327***	-0.020**	-0.373***	0.033***	-0.107***	0.033***	-0.105***
	(0.010)	(0.097)	(0.010)	(0.099)	(0.003)	(0.032)	(0.003)	(0.033)
R&D / Assets	0.964***	3.368***	0.960***	3.346***	0.316***	0.733***	0.315***	0.750***
	(0.027)	(0.219)	(0.027)	(0.221)	(0.009)	(0.072)	(0.009)	(0.073)
Sales Growth	-0.032***	0.149*	-0.033***	0.141*	0.024***	0.023	0.024***	0.022
	(0.009)	(0.081)	(0.009)	(0.082)	(0.003)	(0.027)	(0.003)	(0.027)
Lerner Index	-0.018***	-0.045**	-0.018***	-0.043**	-0.004***	0.004	-0.004***	0.005
	(0.002)	(0.020)	(0.002)	(0.020)	(0.001)	(0.007)	(0.001)	(0.007)
Year FEs		Yes		Yes		Yes		Yes
Industry FEs		Yes		Yes		Yes		Yes
Observations		171,862		171,442		171,862		171,442

TABLE 7
Income Deprivation and Corporate Innovation: Subsamples by Degree of Industry Innovativeness

Table 7 presents the results of the HLM regression, examining the relation between corporate innovation outputs and state income inequality (or state income deprivation) within the highly innovative and lowly innovative industry subsamples. An industry is classified as innovative if the time- and technology-adjusted citation count per patent surpasses the median adjusted citation count across all industries in a specific year. I utilize a 2-digit Standard Industrial Classification. Income inequality and income deprivation are based on the state-level Gini coefficient. In Panel A, the dependent variable is the natural logarithm of the number of patents applied for in a given year. In Panel B, the dependent variable is the natural logarithm of the total citations per patent applied for in a given year. All dependent variables are adjusted for time and technology biases, and all independent variables are lagged by one year. The results for within-state analysis are not reported in Table 7. The inclusion of year and 2-digit SIC industry fixed effects is indicated at the bottom of each model. Standard errors are presented in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Panel A. Quantitative Innovation

Dependent Variable:	ln (1 + Patent Count)			
Industry Innovativeness:	Innovative Industry		Non-Innovative Industry	
	(1)	(2)	(3)	(4)
Income Inequality	0.311**		0.259***	
	(0.139)		(0.088)	
Income Deprivation		0.420***		0.283***
		(0.105)		(0.069)
All firm characteristics	Yes	Yes	Yes	Yes
All state characteristics	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	177,871	177,871	58,867	58,867

Panel B. Qualitative Innovation

Dependent Variable:	ln (1 + Citation per Patent)			
Industry Innovativeness:	Innovative Industry		Non-Innovative Industry	
	(1)	(2)	(3)	(4)
Income Inequality	-0.017		-0.039	
	(0.045)		(0.033)	
Income Deprivation		-0.076**		-0.015
		(0.034)		(0.026)
All firm characteristics	Yes	Yes	Yes	Yes
All state characteristics	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	177,871	177,871	58,867	58,867

TABLE 8
General Robustness Tests

Table 8 presents the general robustness tests for the results of Chapter 5. Income inequality and income deprivation are based on the state-level Gini coefficient. Rows (1a) and (1b) report the significance of income inequality measures after excluding self-citation. In rows (2)-(5), each model uses a different first component of income inequality measures based on the data period and standardization. In rows (6a)-(6c), each model controls for the state tax burden rate. Rows (7a) and (7b) exclude income satisfaction. Rows (8a) and (8b) exclude data from the most recent year, 2018, in each model. Rows (9a) and (9b) exclude firm-year observations with zero patents. All test results are based on the HLM regression. In rows (10a)-(10f), the independent variables are lagged from t-1 to t-3. In rows (11a) and (11b), each model uses the total number of citations up to 5 years after application. All dependent variables are adjusted for time and technology bias (except for row (1) tests), and all independent variables are lagged by one year. The regressions include all firm-level and state-level controls, as presented in Chapter 5. For brevity, the table only reports coefficients on Income Inequality, Income Deprivation, and Tax Burden Rate. Within-state results are not reported in Table 8. Year and 2-digit SIC industry fixed effects are included in each model. Standard errors are presented in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

	ln (1 + Patent Count)			ln (1 + Citation per Patent)		
	Coef.	SE	Obs.	Coef.	SE	Obs.
(1) Exclude self-citations						
(1a) Income Inequality				0.025	(0.150)	177,871
(1b) Income Deprivation				-0.209*	(0.112)	177,871
(2) First Component of Income Inequality (FC)	0.159***	(0.055)	177,871	0.194	(0.018)	177,871
(3) FC without standardization	0.163***	(0.053)	177,871	0.019	(0.017)	177,871
(4) FC with standardization (1917-2018)	0.160***	(0.055)	177,871	0.020	(0.018)	177,871
(5) FC without standardization (1917-2018)	0.186***	(0.060)	177,871	0.016	(0.019)	177,871
(6) Control for tax burden						
(6a) Income Inequality	0.164	(0.143)	170,360	0.006	(0.020)	170,360
Tax Burden Rate	1.641***	(0.511)	170,360	-0.629***	(0.161)	170,360
(6b) Income Inequality (FC)	0.146***	(0.055)	170,360	0.026	(0.018)	170,360
Tax Burden Rate	1.666***	(0.506)	170,360	-0.636***	(0.159)	170,360
(6c) Income Deprivation	0.369***	(0.113)	170,360	-0.063*	(0.039)	170,360
Tax Burden Rate	1.457***	(0.579)	170,360	-0.586**	(0.161)	170,360
(7) Income Deprivation > 0						
(7a) Income Deprivation	0.018***	(0.006)	177,871	-0.002	(0.002)	177,871
(7b) Income Deprivation (Gini99)	-0.009	(0.005)	177,871	-0.007***	(0.002)	177,871
(8) Include patent data up to 2017						
(8a) Income Inequality	0.363**	(0.142)	171,442	-0.025	(0.047)	171,442
(8b) Income Deprivation	0.382***	(0.106)	171,442	-0.061*	(0.035)	171,442
(9) Exclude firm-year where patent count = 0						
(9a) Income Inequality	0.184	(0.422)	43,432	-0.336**	(0.152)	43,432
(9b) Income Deprivation	0.248	(0.310)	43,432	-0.405***	(0.112)	43,432
(10) Varying lagged structure						
(10a) Income Inequality (t-1)	0.311***	(0.139)	177,871	-0.017	(0.045)	177,871
(10b) Income Inequality (t-2)	0.302**	(0.149)	162,520	-0.027	(0.047)	162,520
(10c) Income Inequality (t-3)	0.283*	(0.160)	148,268	-0.071	(0.049)	148,268
(10d) Income Deprivation (t-1)	0.420***	(0.105)	177,871	-0.076**	(0.034)	177,871
(10e) Income Deprivation (t-2)	0.361***	(0.112)	162,520	-0.057	(0.036)	162,520
(10f) Income Deprivation (t-3)	0.296**	(0.120)	148,268	-0.089**	(0.037)	148,268
(11) History Bias in Patent Citations						
(11a) Income Inequality				-0.125	(0.098)	143,468
(11b) Income Deprivation				-0.180**	(0.075)	143,468

TABLE 9
Instrumental Variable Approach: Income Inequality and Quantitative Innovation

Table 9 presents the regression results on the relation between state income inequality and corporate innovation outputs. To ensure that the key variable, income inequality, is independent of other unobservable characteristics affecting the outcome (corporate innovation), I regress income inequality on the instrumental variable of extreme temperature. Extreme Temperature is a dummy variable that equals one if a state's Heating Degree Days (HDD) or Cooling Degree Days (CDD) exceeds one standard deviation of HDD or CDD; otherwise, it is zero. The degree days data covers the period from 1895 to 2017 but does not include Alaska, Hawaii, and the District of Columbia. Column (1) shows the first stage, where the state-level income inequality measure is regressed on the state-level extreme temperature dummy variable. Column (2) shows the second stage, where firm-level innovation (patent count for column (2)) is regressed on the state-level income inequality measure predicted from the first stage regression. Income inequality is based on the state-level Gini coefficient. All firm characteristics are state-year means. All dependent variables are adjusted for time and technology bias, and all independent variables are lagged by one year. The inclusion of year and 2-digit SIC industry is indicated at the bottom of each model. Standard errors are shown in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Instrumental variable	Extreme Temperature: Degrees exceeding one S.D. of HDD or CDD	
Dependent variable	Income Inequality	ln (1 + Patent Count)
	(1)	(2)
Extreme Temperature	0.0004***	
	(0.000)	
$\widehat{\text{Income Inequality}}$		24.850**
		(11.453)
Population	-0.0093***	-0.424**
	(0.000)	(0.197)
Collectivism	0.0056***	-0.635**
	(0.000)	(0.287)
ln (Sales)	0.0531***	0.431***
	(0.006)	(0.112)
ln (PPE / EMP)	0.0151***	-0.112*
	(0.001)	(0.068)
Book Leverage	-0.0591***	-1.926***
	(0.006)	(0.651)
Tobin Q	-0.2480***	-0.385**
	(0.012)	(0.172)
ROA	0.0747***	0.919
	(0.004)	(0.690)
R&D / Assets	-0.0070***	9.555***
	(0.001)	(2.865)
Sales Growth	-0.0093***	-1.822**
	(0.000)	(0.856)
Lerner Index	0.0056***	0.189**
	(0.000)	(0.095)
Year FEs	Yes	Yes
Industry FEs	Yes	Yes
State FEs	Yes	Yes
Observations	177,406	177,406
Adjusted R^2	0.856	0.151

TABLE 10
Political Channels Linking State Income Deprivation to Qualitative Innovation

In Table 10, Panel A presents political channels that may link state-level income deprivation to firm-level innovations. Columns (1), (3), (5), and (7) of each panel show the first stage, where state-level political channel variables are regressed on state-level income deprivation dummy variables. Columns (2), (4), (6), and (8) of each panel show the second stage, where firm-level innovation (patent citations) is regressed on the state-level channel variables predicted from the first stage regressions with the state-level income deprivation measure. Panel B reports overidentification test results. The income deprivation dummy equals one if the state's income deprivation for a given year is greater than zero; otherwise, it is zero. Income deprivation is based on the state-level Gini99 coefficient and welfare expenditure per capita. All firm characteristics are state-year means. All dependent variables are adjusted for time and technology bias, and all independent variables are lagged by one year. The inclusion of year and 2-digit SIC industry is indicated at the bottom of each model. Standard errors are shown in parentheses. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Panel A. Income Deprivation and Qualitative Innovation

Channel Category:	Political Uncertainty						Policy Uncertainty	
Channel:	Winner Margin (WM)		Governor Change (GC)		Absence of Incumbent (AI)		Political Alignment (PA)	
Dependent Variable:	WM	ln (1 + Citation per Patent)	GC	ln (1 + Citation per Patent)	AI	ln (1 + Citation per Patent)	PA	ln (1 + Citation per Patent)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income Deprivation Dummy	0.060***		0.030***		0.154***		-0.028***	
	(0.004)		(0.005)		(0.005)		(0.002)	
$\widehat{\text{Winner Margin}}$		-0.202***						
		(0.063)						
$\widehat{\text{Governor Change}}$				-0.402***				
				(0.126)				
$\widehat{\text{Absence of Incumbent}}$						-0.078***		
						(0.025)		
$\widehat{\text{Political Alignment}}$								0.437***
								(0.137)
All firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,953	43,953	43,953	43,953	43,953	43,953	43,923	43,953
Adjusted R^2	0.252	0.128	0.275	0.128	0.332	0.128	0.522	0.128

Panel B. Overidentification Test

Channel:	Overidentification Test	
Winner Margin (WM)	Sargan	X^2 (3) = 3.9552 (p = 0.2663)
	Basmann	X^2 (3) = 3.9404 (p = 0.2680)
Governor Change (GC)	Sargan	X^2 (3) = 5.6571 (p = 0.1295)
	Basmann	X^2 (3) = 5.6362 (p = 0.1307)
Absence of Incumbent (AI)	Sargan	X^2 (3) = 3.5935 (p = 0.3088)
	Basmann	X^2 (3) = 3.5801 (p = 0.3105)
Political Alignment (PA)	Sargan	X^2 (3) = 6.2148 (p = 0.1016)
	Basmann	X^2 (3) = 6.1919 (p = 0.1026)

FIGURE 1
Two Competing Effects of Income Inequality on Corporate Innovation

The figure illustrates the relation between income inequality and corporate innovation through two types of motivation. Extrinsic motivation, which relies on physical compensation, can result in increased quantitative innovation as individuals strive to enhance their income. On the other hand, intrinsic motivation can drive qualitative innovation through self-determination and personal interest. However, an unfair compensation system has the potential to undermine intrinsic motivation.

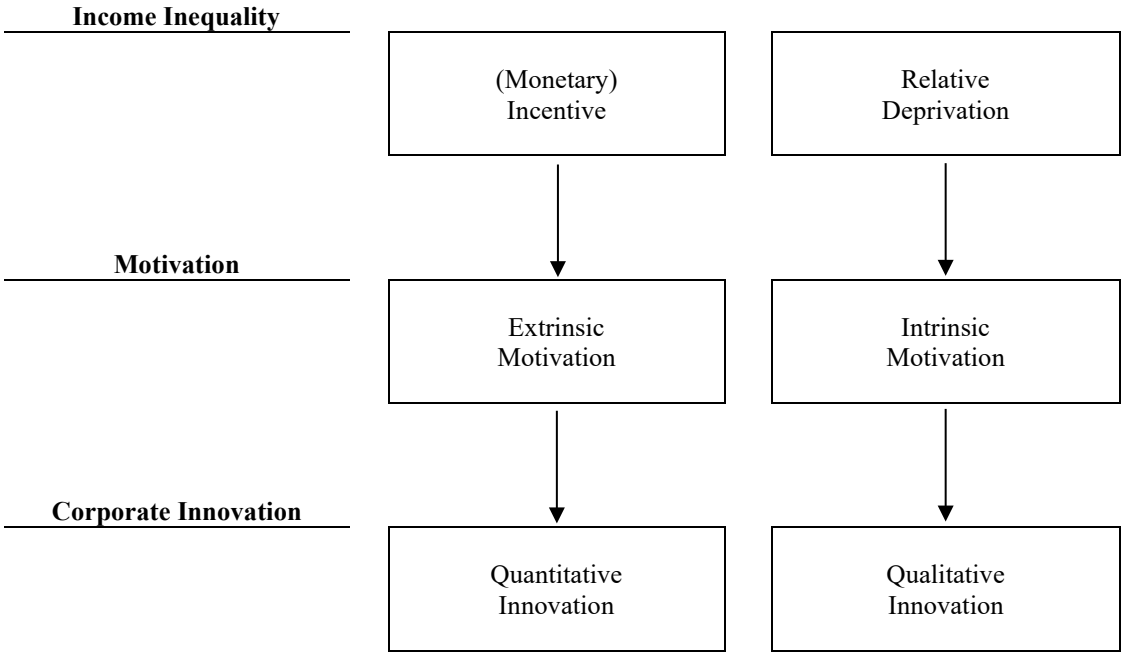
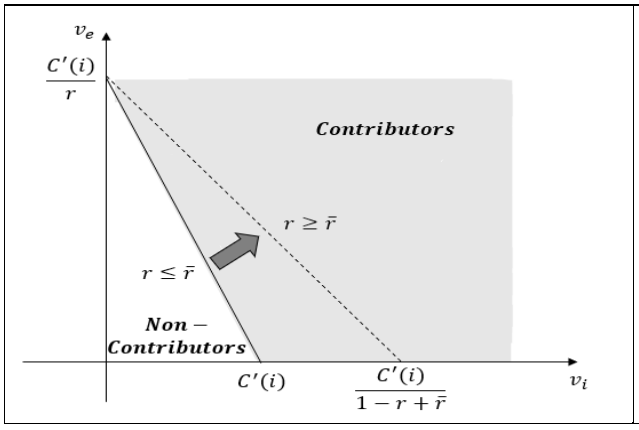


FIGURE 2
Relative Deprivation and Contributors' Distribution

The left-hand side panel figure shows changes in the two-motivational valuation mix with or without relative deprivation. The right-hand side panel figure shows the distribution of monetary incentives and relative deprivation space for contributors and non-contributors. Contributors are shaded in both panels.

(a) The Effect of Relative Deprivation on Motivational Valuation Mix



(b) Contributors' Distribution on Monetary Incentive and Relative Deprivation Space

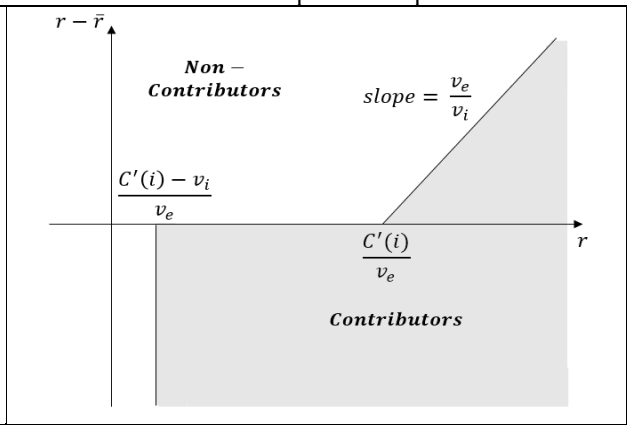


FIGURE 3
Deviation of State-level Income Inequality and Income Deprivation in the US

The left-hand side panel of the figure shows the boxplot of state-level income inequality by year. The right-hand side panel of the figure shows the boxplot of state-level income deprivation by year. The upper and lower hinges of the box represent the 75th and 25th percentiles, respectively. The upper and lower whiskers of the box indicate values above the 75th percentile and below the 25th percentile, extending no further than 1.5 times the interquartile range (IQR). Any data points outside the whiskers are plotted individually as outliers. Income inequality and income deprivation are based on the state-level Gini coefficient.

(a) Income Inequality

(b) Income Deprivation

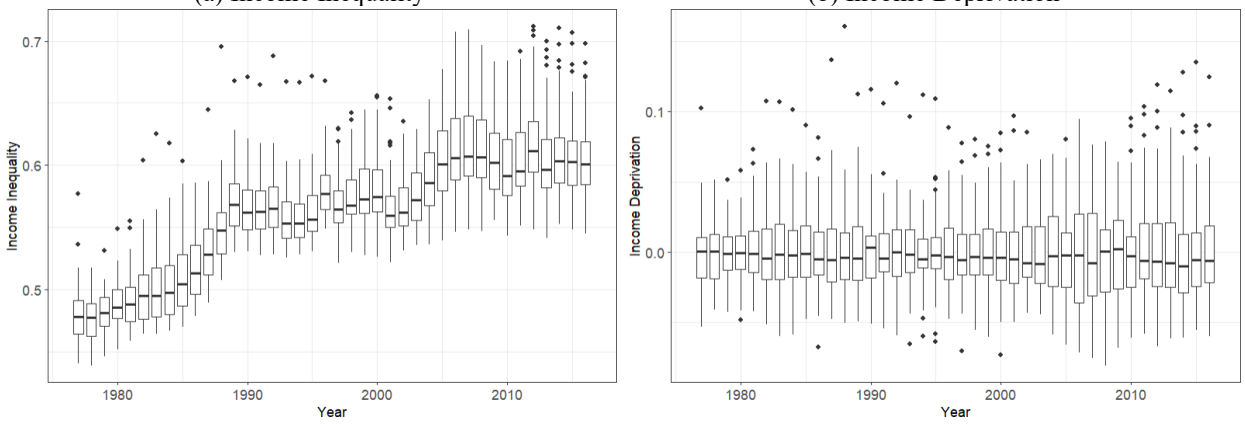


FIGURE 4
State-level Income Inequality and Income Deprivation in the US (2015)

The left-hand panel of the figure shows income inequality by state in 2015. The right-hand panel of the figure shows income deprivation by state in the same year. The deeper the red color, the higher the level of income inequality or income deprivation. Income inequality and income deprivation are based on the state-level Gini coefficient.

(a) Income Inequality

(b) Income Deprivation

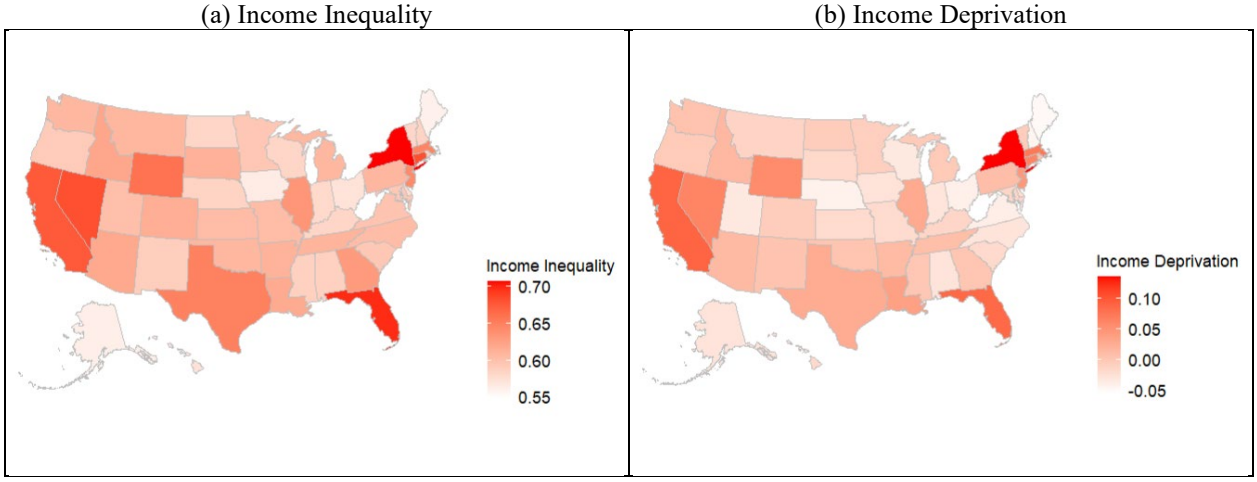


FIGURE 5
Trends of Income Inequality and Income Deprivation (Florida and Washington)

The figure illustrates the historical trends of income inequality and income deprivation in Florida (black) and Washington (gray). The solid line represents state income inequality, while the dotted line represents state income deprivation.

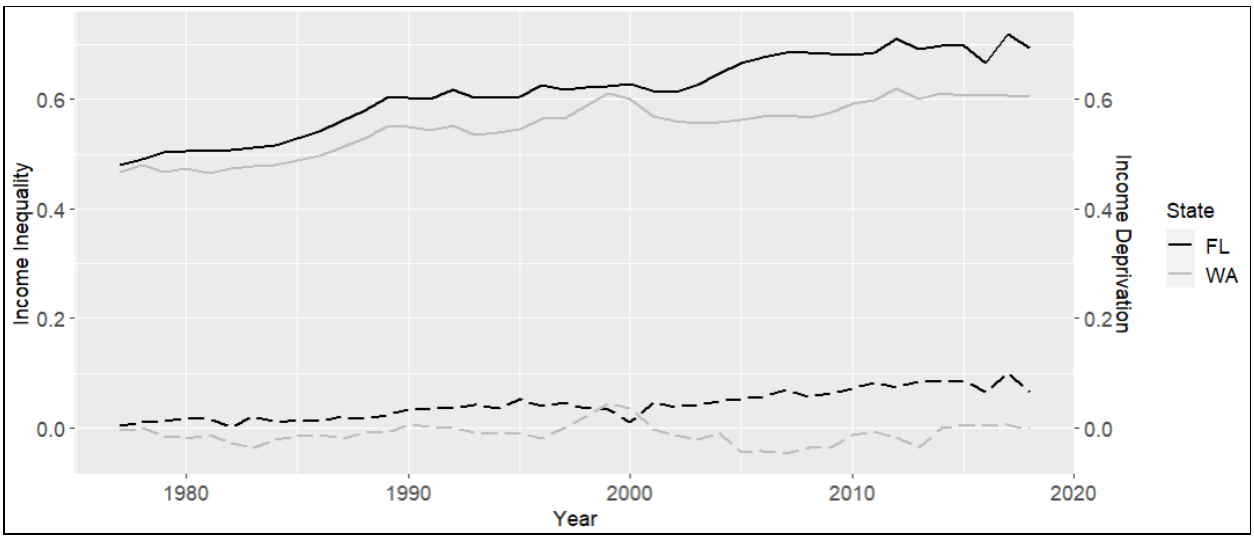
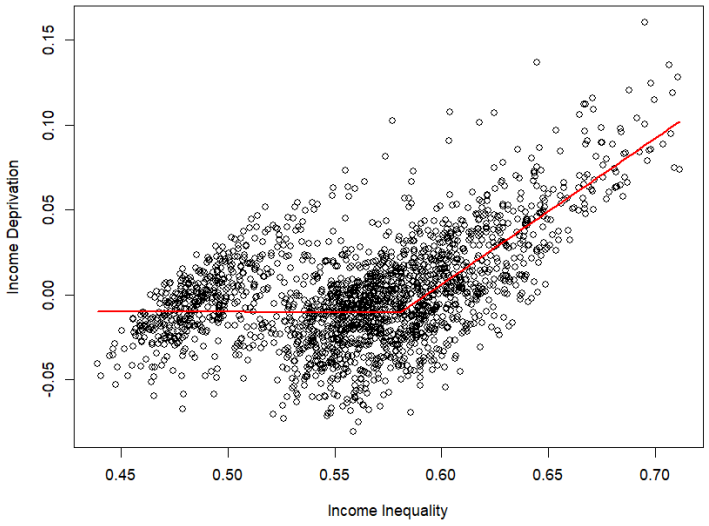


FIGURE 6
Distribution of Income Inequality and Income Deprivation in the US

The figure illustrates the relation between income inequality and income deprivation using state-year data. The curve was generated using the piecewise linear regression model.



APPENDIX A
Detailed Derivations of the Simple Motivation Model with Incentive and Deprivation

In this appendix, I solve the agent's problem expressed as follows:

$$\max_{i \in I} \underbrace{[v_i\{1 - max(0, r - \bar{r})\}}_{\text{Intrinsic Motivation}} + \underbrace{v_e r]}_{\text{Extrinsic Motivation}} i - C(i). \tag{1}$$

This agent's problem is based on Bénabou and Tirole's (2003, 2006) theory of motivations and incentives. The distinguishing feature of this agent's problem compared to Bénabou and Tirole's (2003, 2006) model is the inclusion of income deprivation ($r - \bar{r}$). Previous literature primarily examines the negative impact of relative deprivation resulting from income inequality on intrinsic motivations [Kakwani (1984), Deckop and Cirka (2000), Deaton (2001)]. Therefore, I include a max function of income deprivation, represented as $max(0, r - \bar{r})$, to model the deterioration of intrinsic motivation once the agent feels deprived.

I use an income inequality measure for the monetary incentive rate (r) in the model. The incentive rate is equal to or greater than zero because the agent is extrinsically motivated by monetary incentives [Ryan and Deci (1985, 2000)].

A representative state employee has a preference type $v \equiv (v_i, v_e) \in R^2$, where v_i and v_e are intrinsic and extrinsic valuations, respectively. i is the participation level of innovation from a choice set $I \in R$, and $C(i)$ is the utility cost of choosing i. The first-order condition of the agent's problem in terms of i is as follows:

$$v_i\{1 - max(0, r - \bar{r})\} + v_e r - C'(i) = 0. \tag{2}$$

A representative state employee is a contributor who engages in prosocial behavior through active corporate innovation under the following conditions:

$$v_i\{1 - max(0, r - \bar{r})\} + v_e r \geq C'(i), \tag{3}$$

where the straight boundary line depends on the existence of relative deprivation.

When relative deprivation exists, that is, $r - \bar{r} > 0$, the contributor group comprises all agents for which

$$v_i\{1 - (r - \bar{r})\} + v_e r \geq C'(i). \tag{4}$$

$$v_i \frac{\{1-(r-\bar{r})\}}{r} + v_e \geq \frac{C'(i)}{r} \tag{5}$$

$$v_e \geq -\frac{\{1-(r-\bar{r})\}}{r} v_i + \frac{C'(i)}{r} \tag{6}$$

In the absence of relative deprivation, that is, $r - \bar{r} \leq 0$, the contributor group consists of all agents for which

$$v_i + v_e r \geq C'(i). \tag{7}$$

$$v_e \geq -\frac{1}{r} v_i + \frac{C'(i)}{r} \tag{8}$$

Equations (6) and (8) are plotted on a two-dimensional plane of v_e and v_i, as shown in Figure 2(a). The grayed area becomes smaller once relative deprivation exists. This figure suggests that once the representative state employee feels deprived, they are less likely to become a contributor who produces more innovative outcomes.

Equations (4) and (7) can be rearranged into the equation for monetary incentives (r) and relative deprivation ($r - \bar{r}$). First, when relative deprivation exists, equation (4) is rearranged as follows:

$$\{1 - (r - \bar{r})\} + \frac{v_e}{v_i} r \geq \frac{C'(i)}{v_i}. \tag{9}$$

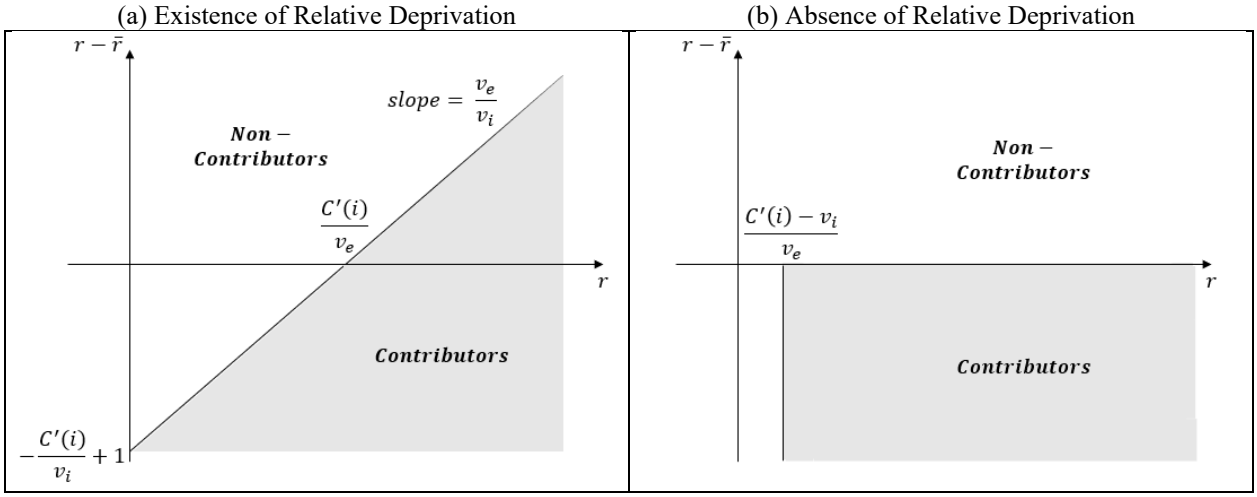
$$(r - \bar{r}) \leq \frac{v_e}{v_i} r - \frac{C'(i)}{v_i} + 1 \tag{10}$$

Second, in the absence of relative deprivation, equation (7) is rearranged as follows:

$$r \geq \frac{C'(i) - v_i}{v_e}. \tag{11}$$

Equations (10) and (11) are plotted on a two-dimensional plane of monetary incentives (r) and relative deprivation ($r - \bar{r}$), as shown in Figure A1. Merging the panels (a) and (b) of Figure A1 results in Figure 2(b).

FIGURE A1. Contributors' Distribution on Monetary Incentive and Relative Deprivation



APPENDIX B
Measures of Income Inequality and Income Deprivation

Based on the theoretical framework, income inequality as a monetary incentive enhances quantitative innovation due to extrinsic motivation, while income deprivation undermines qualitative innovation due to intrinsic motivation. Income deprivation is defined as the income inequality of a corresponding state minus that of comparison states with similar levels of welfare expenditure. It is plausible that high income deprivation could be linked to high monetary incentives, thereby fostering more quantitative innovation. However, higher deprivation compared to states with similar welfare expenditure levels may discourage average income earners in that state. Therefore, for a state to foster both quantitative and qualitative innovation, it would ideally maintain a moderate level of income inequality lower than that of states with comparable welfare expenditures.

To enhance clarity and comprehension of these measures, Panel A of Figure A2 presents a detailed illustration of the inequality [Gini] and relative deprivation [RD(Gini)] measures for several states, specifically Florida and Washington, in 1995 and 2010. The accompanying bar charts illustrate state-level welfare expenditure per capita in 1995 and 2010, highlighting Florida and Washington in red, comparison states in blue, and all others in gray. For instance, in 1995, Florida had an inequality of 0.605, while comparison states such as Kansas, Indiana, North Carolina, Oklahoma, and Arizona showed similar levels of per capita welfare expenditure. The average income inequality for these comparison states was 0.552, resulting in Florida's relative deprivation being calculated as 0.053 (0.605 minus 0.552). In the same year, Washington had an inequality of 0.546, while comparison states such as North Dakota, Illinois, Tennessee, Oregon, and South Carolina showed similar levels of per capita welfare expenditure. The average income inequality for these comparison states was 0.556, resulting in Washington's relative deprivation being calculated as -0.010 (0.546 minus 0.556).

Panel B of Figure A2 depicts changes in income inequality and income deprivation in Florida, Hawaii, Massachusetts, and Washington from 1977 to 2018. It shows that states with high income inequality are more likely to experience relative deprivation. Furthermore, the statistics from Figure A2 indicate that maintaining lower income inequality compared to peers, rather than merely increasing welfare expenditure, is crucial for reducing deprivation and promoting an innovation-friendly environment.

Welfare expenditure is endogenous to income inequality. However, this paper uses welfare expenditure solely to identify comparison states with similar levels of welfare expenditure. Therefore, the difference in income inequality between the state and the comparison states has little to do with the size of the state's total welfare expenditure. Considering that the state's higher income inequality compared to the average income inequality of the comparison states is defined as relative deprivation, the state's relative deprivation is less likely to be related to the size of the welfare expenditure. Instead, the efficiency of welfare expenditure becomes crucial after the spending has occurred. Park (2011) explores the efficiency of welfare expenditures in different countries, grouping them based on their performance in reducing welfare inefficiency. If a state alleviates more income inequality than other states that spend the same amount on welfare, it achieves welfare expenditure efficiency. Conversely, if a state experiences welfare inefficiency, employees in that state may feel relative deprivation. O'Connor (1989) finds that

while total welfare expenditure levels are comparable to those in other countries, the composition of expenditures and policy orientation can differ significantly. Moreover, demographic factors, such as class and citizenship, can also differentiate the distribution of benefits. While per capita spending alone may be limited in fully explaining welfare efficiency, I explore how the composition of public welfare expenditure relates to relative deprivation. Cash assistance is a crucial component of the state's welfare expenditure. Tabor (2002) finds that cash assistance programs are less likely to distort prices and provide greater discretion to low-income recipients. Joumard, Pisu, and Bloch (2012) report that cash transfers have a redistributive effect that reduces income dispersion. Additionally, Bastagli, Coady, and Gupta (2012) highlight that well-targeted conditional cash transfer programs aimed at the poorest households are the most cost-effective in lowering income inequality. Following the literature, I focus on the proportion of cash assistance programs, which include Temporary Assistance for Needy Families (TANF) and Supplemental Security Income (SSI), in state welfare expenditure.

Panel A of Figure A3 presents the correlation between relative deprivation, measured by cumulative years of deprivation per state as defined in this study, and the average share of cash assistance spending at the state level. The average cash assistance spending share indicates the proportion of state government expenditures allocated to cash assistance relative to total welfare spending. While public welfare benefits are typically administered at the state level, in a few states like California, these programs are managed by local county governments. Due to data limitations and incomplete information at the local government level, further analysis is not included. Nonetheless, the overall findings suggest a negative relation between the share of cash assistance and relative deprivation.

Panel B of Figure A3 illustrates the historical trends in relative deprivation and the share of cash assistance spending in Florida and Washington. In Panel B(a), Florida consistently allocates a lower proportion of its spending to cash assistance programs compared to Washington, yet experiences higher levels of deprivation. Importantly, Panel B(b) shows that while Florida's cash assistance spending remains lower relative to its counterparts, Washington tends to allocate a higher share of its spending to these programs. This suggests that states with a higher proportion of cash assistance programs are less prone to relative deprivation, even when their overall welfare expenditure levels are similar to those of comparison states.[19] This implies a potential mechanism for reducing income inequality [Tabor (2002), Bastagli et al. (2012), Joumard et al. (2012), International Monetary Fund (2019)].

FIGURE A2. Income Inequality and Income Deprivation

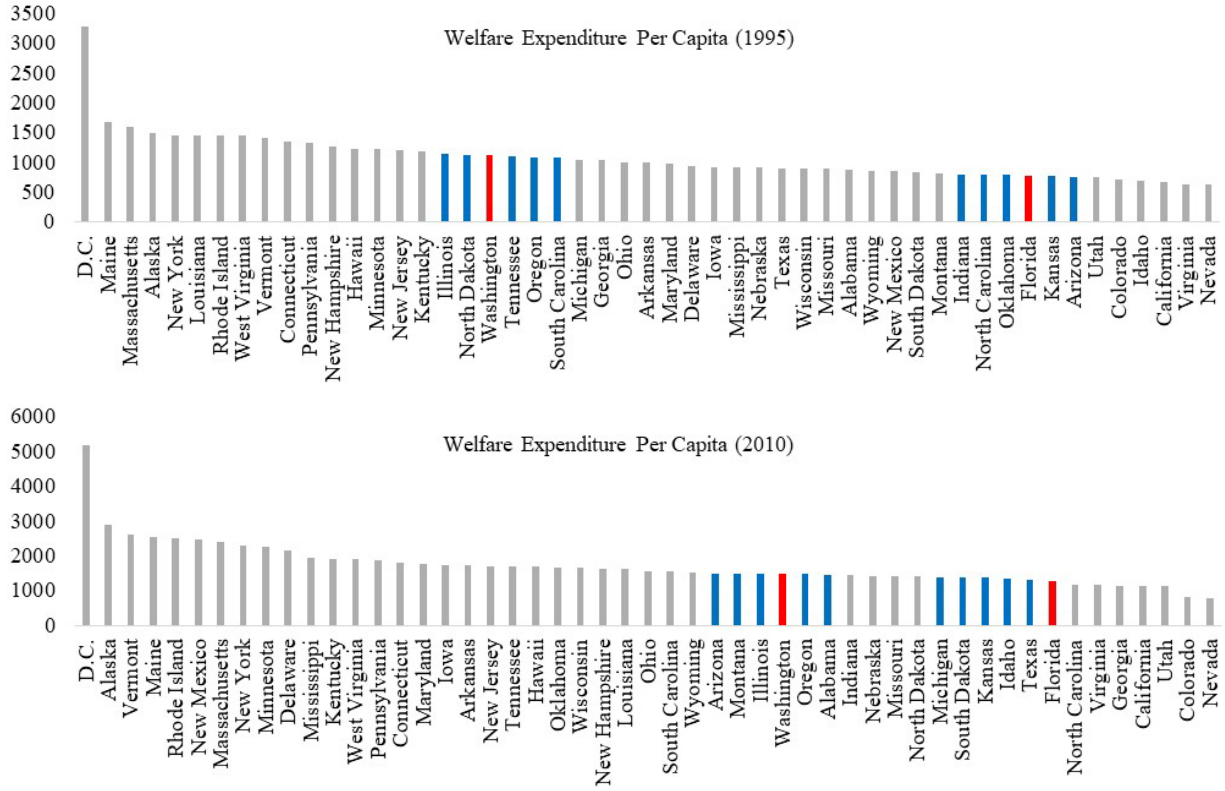
Panel A of Figure A2 provides a detailed illustration of income inequality and deprivation in Florida and Washington for 1995 and 2010. The accompanying bar charts highlight Florina and Washington in red, comparison states in blue, and all others in gray. Panel B of Figure A2 illustrates changes in income inequality and deprivation of Florida, Hawaii, Massachusetts, and Washington from 1977 to 2018.

[19] Following the welfare reform through the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996, the Aid to Families with Dependent Children (AFDC) program was replaced by the Temporary Assistance for Needy Families (TANF) program. This change introduced block grants for states. Although it gave states more flexibility, cash assistance has consequently decreased due to several restrictions, such as mandatory work-related activities for recipients and time limits on receiving assistance.

Panel A. Presentation of Income Inequality and Income Deprivation

Year	State	RD(Gini) (A-B)	Gini (A)	Avg Gini of 5 Comparison States (B)	Welfare Similar State 1	Welfare Similar State 2	Welfare Similar State 3	Welfare Similar State 4	Welfare Similar State 5
					Gini				
1995	Florida ($789)	0.053	0.605	0.552	Kansas ($778)	Indiana ($807)	North Carolina ($807)	Oklahoma ($807)	Arizona ($769)
					0.553	0.539	0.540	0.564	0.564
	Washington ($1130)	-0.010	0.546	0.556	North Dakota ($1131)	Illinois ($1143)	Tennessee ($1107)	Oregon ($1092)	South Carolina ($1088)
					0.553	0.574	0.561	0.550	0.544
2010	Florida ($1294)	0.072	0.682	0.610	Texax ($1314)	Idaho ($1332)	Kansas ($1371)	South Dakota ($1395)	Michigan ($1396)
					0.631	0.629	0.591	0.599	0.597
	Washington ($1482)	-0.013	0.592	0.605	Oregon($1475)	Illinois ($1497)	Montana ($1499)	Arizona ($1500)	Alabama ($1459)
					0.583	0.620	0.613	0.618	0.591

* Welfare Expenditure per Capita is presented in parantheses.



Panel B. Change in Income Inequality and Deprivation (Examples)

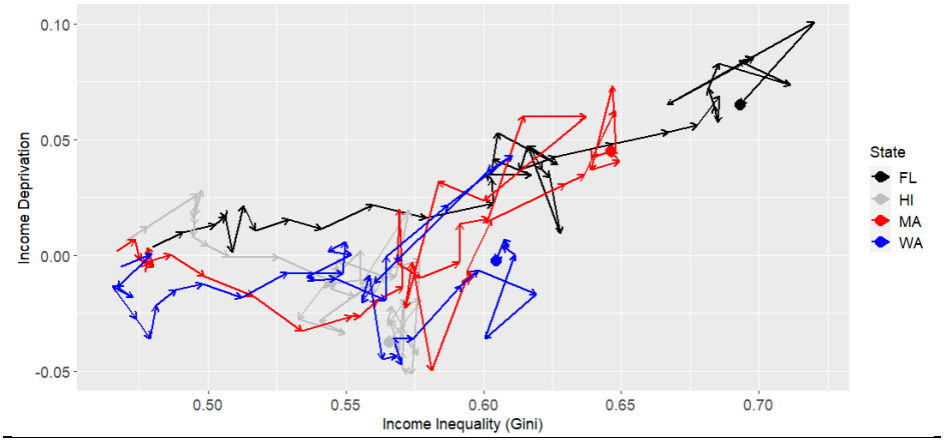
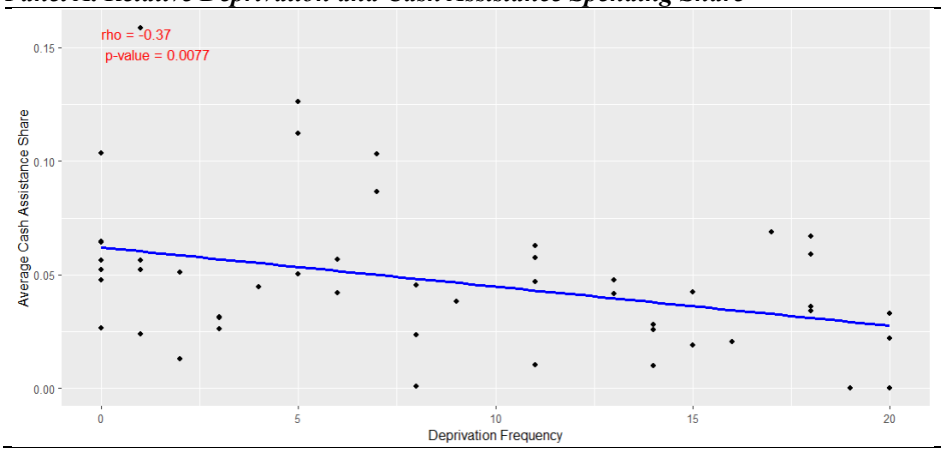


FIGURE A3. Relative Deprivation and Cash Assistance Program

In Figure A3, Panel A shows the correlation between relative deprivation and the average cash assistance spending share at the state level. Relative deprivation is measured by the number of years each state experiences deprivation, as defined in this paper. The average cash assistance spending share is the average proportion of state government cash assistance spending out of total welfare expenditures. Panel B presents the historical trend of relative deprivation and cash assistance spending share, with examples from Florida and Washington. Panel B(a) shows the relative deprivation and cash assistance spending share at the state level, while Panel B(b) shows the difference between the corresponding state's cash assistance spending share and the average cash assistance spending share of its comparison states. The sample period is from 1997 to 2018.

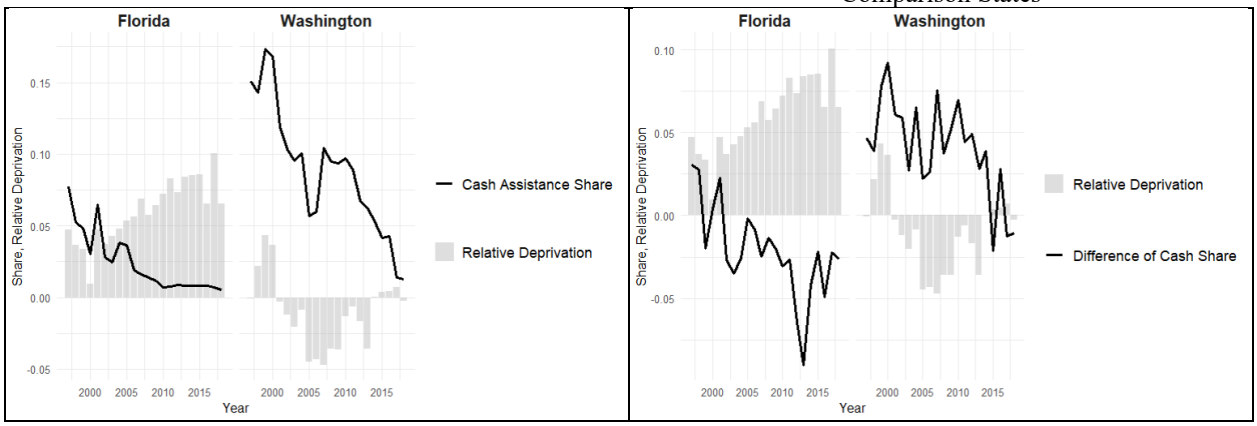
Panel A. Relative Deprivation and Cash Assistance Spending Share



Panel B. Historical Trend of Relative Deprivation and Cash Assistance Spending Share (Examples)

(a) Cash Assistance Spending

(b) Difference in Cash Assistance Spending Compared to Comparison States



APPENDIX C
Variable Definition

Variable	Definition
Measures of Innovation	
ln (1 + Patent Count)	Natural logarithm of one plus firm i's number of patents applied for during the year
ln (1 + Citation/Patent)	Natural logarithm of one plus firm i's total number of citations per patent applied for during the year
State-level Variables	
Top 10% Share	Top 10% income share in the state where firm i is headquartered during the year
Top 5% Share	Top 5% income share in the state where firm i is headquartered during the year
Top 1% Share	Top 1% income share in the state where firm i is headquartered during the year
Top 0.5% Share	Top 0.5% income share in the state where firm i is headquartered during the year
Top 0.1% Share	Top 0.1% income share in the state where firm i is headquartered during the year
Top 0.01% Share	Top 0.01% income share in the state where firm i is headquartered during the year
AvgTop	Average income shares from the top 10% to the top 1% in the state where firm i is headquartered during the year
Gini	Gini coefficient of the state where firm i is headquartered during the year
Gini99	Gini coefficient of the bottom 99% income distribution of the state where firm i is headquartered during the year
FC (Income Inequality)	The first principal component is computed based on nine standardized income inequality measures. These measures include the income shares of the top 10%, top 5%, top 1%, top 0.5%, top 0.1%, and top 0.01% of the population. Additionally, the average income shares from the top 10% to the top 2% are considered, along with the Gini coefficient and the Gini coefficient of the bottom 99% of the income distribution.
RD (Top 10%)	Top 10% income share of state j minus the average top 10% income share among five welfare expenditure-proximate states. The welfare expenditure proximity is measured by state-level welfare expenditure per capita.
RD (Top 1%)	Top 1% income share of state j minus the average top 1% income share among five welfare expenditure-proximate states. The welfare expenditure proximity is measured by state-level welfare expenditure per capita.
RD (Gini)	Gini coefficient of state j minus the average Gini coefficient among five welfare expenditure-proximate states. The welfare expenditure proximity is measured by state-level welfare expenditure per capita.
RD (Gini 99)	Gini99 of state j minus the average Gini99 among five welfare expenditure-proximate states. The welfare expenditure proximity is measured by state-level welfare expenditure per capita.
Social Deprivation Index (SDI)	The SDI is a composite measure based on seven demographic attributes derived from the 2011–2015 five-year American Community Survey developed by the Robert Graham Center. These attributes include the percent of the population in poverty, the percent of the population with less than 12 years of education, the percent of the unemployed population, the percent of the population living in renter-occupied housing, the percent of the population living in crowded housing units, the percent of single-parent households, and the percent of the population with no car. The SDI assigns ranks to each census tract, with 1 indicating the least disadvantaged and 100 indicating the most disadvantaged. One of the strengths of the SDI is its calculation in four different geographic areas, which enables matching with Compustat's firm ZIP code. Furthermore, the SDI exhibits a significantly high correlation with income inequality and social associations among various aspects of deprivation (Glassman 2020). Therefore, it best reflects the characteristics of relative deprivation expressed in this paper.

APPENDIX C (Continued)
Variable Definition

Variable	Definition
Area Deprivation Index (ADI)	The ADI is a composite measure of 17 socioeconomic attributes, including income, education, employment, housing, and household, derived from the 2011–2015 five-year American Community Survey developed by the University of Wisconsin–Madison. The ADI is measured at the national and state levels. The national ADI ranks each block group from 1 (least disadvantaged) to 100 (most disadvantaged), while the state ADI ranks each block group from 1 (least disadvantaged) to 10 (most disadvantaged). The national ADI effectively captures overall regional deprivation-related characteristics, including income inequality.
Population	Natural logarithm of state j's population during the year
Collectivism	State-level collectivism index based on eight measures: the percentage of people living alone, the ratio of people carpooling to work compared to driving alone, the proportion of divorce rate to marriage rate, the percentage of older people living alone, the share of households with grandchildren, the percentage of people with no religious affiliation, the average percentage of Libertarian votes over the last four presidential elections, and the percentage of self-employed people. The index was developed by Vandello and Cohen (1999).
Political Uncertainty	I collect U.S. gubernatorial election data from the Guide to U.S. Elections (CQ Press 2016) and Dave Leip's Atlas of U.S. Presidential Elections. I construct the gubernatorial election data from 1975 to 2020, which includes the election year, elected candidate/party, run-up candidate/party, winning margin, term limit, governor change, absence of an incumbent, and re-elected candidate/party. The politically uncertain election year is defined based on three criteria: winner margin (WM), governor change (GC), and absence of an incumbent (AI). (1) Winner Margin (WM): This is a dummy variable indicating state political uncertainty. I sort all the elections based on the vote difference between the winner and the runner-up and set the bottom tercile as the period of high political uncertainty, defined as WM. (2) Governor Change (GC): This is a dummy variable indicating state political uncertainty. It represents cases where the governor changed with a winner margin of less than 5%. (3) Absence of Incumbent (AI): This is a dummy variable indicating state political uncertainty. It represents cases where there was an absence of the incumbent governor, except for the term-limit issue.
Policy Uncertainty	I use the political alignment index (PA) of Kim, Pantzalis, and Park (2012) and Kim and Park (2021). This is a state-level measure of alignment with the President's party, calculated as the equally weighted portions of each of the state's delegations in the two chambers of Congress as follows: $PAI_{jt} = 0.25 \times Senate_{jt} + 0.25 \times House_{jt} + 0.25 \times Governor_{jt} + 0.25 \times (0.5 \times StateSenate_{jt} + 0.5 \times StateHouse_{jt})$. For the channel analysis, PA equals one if the political alignment index is higher than the previous year; otherwise, it is zero.
Innovative Industry	An industry is considered innovative if the time and technology-adjusted citation count per patent in that sector is higher than the median adjusted citation count per patent across all industries in a given year. I utilize a two-digit Standard Industrial Classification.
Tax Burden	State-level tax burden rate per capita is calculated as total taxes divided by personal income. Total taxes include taxes paid to the individual's own state as well as taxes paid to other states.

APPENDIX C (Continued)
Variable Definition

Variable	Definition
Firm-level Variables in Baseline Specifications	
ln (Sales)	Natural logarithm of one plus firm i's sales in millions of dollars
ln (PPE / EMP)	Natural logarithm of one plus firm i's property, plant, and equipment per employee in thousands of dollars
Book Leverage	The ratio of firm i's total long-term debt and current liabilities to its total assets
Tobin Q	The ratio of firm i's market value to its book value of assets
ROA	The ratio of firm i's operating income before depreciation to its total assets
R&D / Assets	Firm i's research and development expenditure scaled by its book values. Missing values coded with zero.
Sales Growth	Log transformation of sales divided by prior year sales
Lerner Index	The ratio of firm i's sales less the cost of goods sold less the total administrative and general expense to its sales. Missing total administrative and general expenses coded with zero.

REFERENCES

Aghion, P., U. Akcigit, A. Bergeaud, R. Blundell, and D. Hemous. "Innovation and Top Income Inequality." *Review of Economic Studies*, 01 (2018), 1–49.

Alvaredo, F. "A Note on the Relationship between Top Income Shares and the Gini Coefficient." *Economics Letters*, 110 (2011), 274–277.

Atkinson, A. B., T. Piketty, and E. Saez. "Top Incomes in the Long Run of History." *Journal of Economic Literature*, 49 (2011), 3–71.

Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu. "Foreign Competition and Domestic Innovation: Evidence from US Patents." *American Economic Review: Insights*, 2 (2020), 357–374.

Balsmeier, B., L. Fleming, and G. Manso. "Independent Boards and Innovation." *Journal of Financial Economics*, 123 (2017), 536–557.

Bastagli, F., D. Coady, and S. Gupta. "Income Inequality and Fiscal Policy." *Staff Discussion Notes*, 12 (2012), 1.

Bénabou, R., and J. Tirole. "Intrinsic and Extrinsic Motivation." *Review of Economic Studies*, 70 (2003), 489–520.

Bénabou, R., and J. Tirole. "Incentives and Prosocial Behavior." *American Economic Review*, 96 (2006), 1652–1678.

Bhattacharya, U., P.-H. Hsu, X. Tian, and Y. Xu. "What Affects Innovation More: Policy or Policy Uncertainty?" *Journal of Financial and Quantitative Analysis*, 52 (2017), 1869–1901.

Buss, T. F. "The Effect of State Tax Incentives on Economic Growth and Firm Location Decisions: An Overview of the Literature." *Economic Development Quarterly*, 15 (2001), 90–105.

Cerasoli, C. P., J. M. Nicklin, and M. T. Ford. "Intrinsic Motivation and Extrinsic Incentives Jointly Predict Performance: A 40-Year Meta-Analysis." *Psychological Bulletin*, 140 (2014), 980–1008.

Chen, Y., E. J. Podolski, S. G. Rhee, and M. Veeraraghavan. "Local Gambling Preferences and Corporate Innovative Success." *Journal of Financial and Quantitative Analysis*, 49 (2014), 77–106.

Chen, Y., P. Y. Dou, S. G. Rhee, C. Truong, and M. Veeraraghavan. "National Culture and Corporate Cash Holdings around the World." *Journal of Banking & Finance*, 50 (2015), 1–18.

Chetty, R., N. Hendren, P. Kline, and E. Saez. "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *The Quarterly Journal of Economics*, 129 (2014), 1553–1623.

Chino, A. "Do Labor Unions Affect Firm Payout Policy?: Operating Leverage and Rent Extraction Effects." *Journal of Corporate Finance*, 41 (2016), 156–178.

Chui, A. C. W., S. Titman, and K. C. J. Wei. "Individualism and Momentum around the World." *The Journal of Finance*, 65 (2010), 361–392.

Cingano, F. "Trends in Income Inequality and Its Impact on Economic Growth."

Çolak, G., A. Durnev, and Y. Qian. "Political Uncertainty and IPO Activity: Evidence from U.S. Gubernatorial Elections." *Journal of Financial and Quantitative Analysis*, 52 (2017), 2523–2564.

Dasgupta, S., J. Emmerling, and S. Shayegh. “Inequality and Growth Impacts from Climate Change - Insights from South Africa.” *Resources for the Future*, (2020), 1–26.
Deaton, A. “Relative Deprivation, Inequality, and Mortality.” NBER.
Deci, E. L., and R. M. Ryan. “Intrinsic Motivation and Self-Determination in Human Behavior.” New York: Plnum.
Deckop, J. R., and C. C. Cirka. “The Risk and Reward of a Double-Edgedsword: Effects of a Merit Payprogram on Intrinsic Motivation.” *Nonprofit and Voluntary Sector Quarterly*, 29 (2000), 400–418.
Deininger, K., and L. Squire. “Economic Growth and Income Inequality: Reexamining the Links.” *Finance & Development*, 34 (1997), 38–41.
Dell, M., B. F. Jones, and B. A. Olken. “Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates.” *American Economic Review*, 99 (2009), 198–204.
Desai, M. A., and D. Dharmapala. “Corporate Tax Avoidance and High-Powered Incentives.” *Journal of Financial Economics*, (2006).
Diffenbaugh, N. S., and M. Burke. “Global Warming Has Increased Global Economic Inequality.” *Proceedings of the National Academy of Sciences*, 116 (2019), 9808–9813.
Duong, H. N., J. H. Nguyen, M. Nguyen, and S. G. Rhee. “Navigating through Economic Policy Uncertainty: The Role of Corporate Cash Holdings.” *Journal of Corporate Finance*, 62 (2020), 101607.
Fang, V. W., X. Tian, and S. Tice. “Does Stock Liquidity Enhance or Impede Firm Innovation?: Does Stock Liquidity Enhance or Impede Firm Innovation?” *The Journal of Finance*, 69 (2014), 2085–2125.
Frank, M. “A New State-Level Panel of Annual Inequality Measures Over The Period 1916-2005.” *Journal of Business Strategies*, 31 (2014), 241–263.
Frank, M. W. “Inequality and Growth in the United States: Evidence from a New State-Level Panel of Income Inequality Measures.” *Economic Inquiry*, 47 (2009), 55–68.
Gomes-Casseres, B., J. Hagedoorn, and A. B. Jaffe. “Do Alliances Promote Knowledge Flows?” *Journal of Financial Economics*, (2006), 29.
Graham, J. R., and A. L. Tucker. “Tax Shelters and Corporate Debt Policy.” *Journal of Financial Economics*, (2006).
Greene, W. H. “Econometric Analysis.” 8th Edition.:. New York, NY: Pearson.
Griffin, D., K. Li, and T. Xu. “Board Gender Diversity and Corporate Innovation: International Evidence.” *Journal of Financial and Quantitative Analysis*, 56 (2021a), 123–154.
Griffin, D., O. Guedhami, K. Li, and G. Lu. “National Culture and the Value Implications of Corporate Environmental and Social Performance.” *Journal of Corporate Finance*, 71 (2021b), 102–123.
Hall, B., A. Jaffe, and M. Trajtenberg. “The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools.” Cambridge, MA: National Bureau of Economic Research.
Hall, B. H., A. B. Jaffe, and M. Trajtenberg. “Market Value and Patent Citations.” 36 (2005), 16–38.
He, J. (Jack), and X. Tian. “The Dark Side of Analyst Coverage: The Case of Innovation.” *Journal of Financial Economics*, 109 (2013), 856–878.
Hennessy, C. A., and T. M. Whited. “Debt Dynamics.” *The Journal of Finance*, 60 (2005), 1129–1165.
Hirshleifer, D., A. Low, and S. H. Teoh. “Are Overconfident CEOs Better Innovators?” *The Journal of Finance*, 67 (2012), 1457–1498.

Hirshleifer, D., P.-H. Hsu, and D. Li. “Innovative Originality, Profitability, and Stock Returns.” *The Review of Financial Studies*, 31 (2018), 2553–2605.
International Monetary Fund. “A Strategy for IMF Engagement on Social Spending.” Washington, D.C.: International Monetary Fund.
Iyer, G., and D. A. Soberman. “Social Responsibility and Product Innovation.” *Marketing Science*, 35 (2016), 727–742.
James, G., D. Witten, T. Hastie, and R. Tibshirani. “An Introduction to Statistical Learning.” New York, NY: Springer.
Joumard, I., M. Pisu, and D. Bloch. “Tackling Income Inequality: The Role of Taxes and Transfers.” *OECD Journal: Economic Studies*, 2012 (2012), 37–70.
Julio, B., and Y. Yook. “Political Uncertainty and Corporate Investment Cycles.” *Journal of Finance*, 67 (2012), 45–83.
Kakwani, N. “The Relative Deprivation Curve and Its Applications.” *Journal of Business & Economic Statistics*, 2 (1984), 384–394.
Kim, C. (Francis), C. Pantzalis, and J. Chul Park. “Political Geography and Stock Returns: The Value and Risk Implications of Proximity to Political Power.” *Journal of Financial Economics*, 106 (2012), 196–228.
Kim, Y., and J. C. Park. “Presidential Power and Stock Returns.” *Financial Management*, (2021), 1–45.
Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. “Technological Innovation, Resource Allocation, and Growth.” *Quarterly Journal of Economics*, 132 (2017), 665–712.
Kong, D., B. Zhang, and J. Zhang. “Higher Education and Corporate Innovation.” *Journal of Corporate Finance*, 72 (2022), 102165.
Korotayev, A. V., and A. R. Shishkina. “Relative Deprivation as a Factor of Sociopolitical Destabilization: Toward a Quantitative Comparative Analysis of the Arab Spring Events.” *Cross-Cultural Research*, 54 (2020), 296–318.
Krueger, A. B. “Inequality, Too Much of a Good Thing.” CEPS.
Ku, H., and T. C. Salmon. “The Incentive Effects of Inequality: An Experimental Investigation.” *Southern Economic Journal*, 79 (2012), 46–70.
Kuhn, J., K. Younge, and A. Marco. “Patent Citations Reexamined.” *RAND Journal of Economics*, 51 (2020), 109–132.
Leigh, A. “How Closely Do Top Income Shares Track Other Measures of Inequality?” *The Economic Journal*, 117 (2007), F619–F633.
Lerner, J., and A. Seru. “The Use and Misuse of Patent Data: Issues for Finance and Beyond.” *Review of Financial Studies*, (2021), 1–38.
Li, K., D. Griffin, H. Yue, and L. Zhao. “National Culture and Capital Structure Decisions: Evidence from Foreign Joint Ventures in China.” *Journal of International Business Studies*, 42 (2011), 477–503.
Liang, H., and L. Renneboog. “On the Foundations of Corporate Social Responsibility: On the Foundations of Corporate Social Responsibility.” *The Journal of Finance*, 72 (2017), 853–910.
Majeed, A. “Relative Deprivation and Political Behaviour.” *The Indian Journal of Political Science*, 40 (1979), 140–155.
Manso, G. “Motivating Innovation.” *Journal of Finance*, 66 (2011), 1823–1860.
Marx, N. de L.-L. “Weather Shocks, Income and Inequality.” Paris School of Economics.

Miao, M., Y. Zhang, and S. Zheng. “Within-Firm Wage Inequality and Corporate Innovation: Evidence from China’s Listed Firms.” *Emerging Markets Finance and Trade*, 56 (2020), 796–819.
Miguel, E., S. Satyanath, and E. Sergenti. “Economic Shocks and Civil Conflict: An Instrumental Variables Approach.” *Journal of Political Economy*, 112 (2004), 725–753.
Miller, M. H. “Debt and Taxes.” *The Journal of Finance*, 32 (1977), 261.
Mueller, H. M., P. P. Ouimet, and E. Simintzi. “Within-Firm Pay Inequality.” *Review of Financial Studies*, 30 (2017), 3605–3635.
Nguyen, L. H., and S. Holmes. “Ten Quick Tips for Effective Dimensionality Reduction.” *PLOS Computational Biology*, 15 (2019), e1006907.
Nidumolu, R., C. K. Prahalad, and M. R. Rangaswami. “Why Sustainability Is Now the Key Driver of Innovation.” *Harvard Business Review*, (2009).
O’connor, J. S. “Welfare Expenditure and Policy Orientation in Canada in Comparative Perspective.” *Canadian Review of Sociology/Revue Canadienne de Sociologie*, 26 (1989), 127–150.
Ostry, J., A. Berg, and C. Tsangarides. “Redistribution, Inequality, and Growth.” Washington, DC: International Monetary Fund.
Park, K. D. “The Efficiency in Welfare Expenditure and Economic Growth.” *The Korean Journal of Policy Studies*, 26 (2011), 129–146.
Pettigrew, T. F. “Samuel Stouffer and Relative Deprivation.” *Social Psychology Quarterly*, 78 (2015), 7–24.
Piketty, T., and E. Saez. “Income Inequality in the United States, 1913-1998.” *The Quarterly Journal of Economics*, 118 (2003), 1–41.
Pirinsky, C., and Q. Wang. “Does Corporate Headquarters Location Matter for Stock Returns?” *Journal of Finance*, 61 (2006), 1991–2015.
Raudenbush, S. W., and A. S. Bryk. “Hierarchical Linear Models: Applications and Data Analysis Methods.” 2nd Edition.:. Thousand Oaks, CA: Sage Publications.
Runciman, W. G. “Relative Deprivation and Social Justice.” London: Routledge & Kegan Paul.
Ryan, R. M., and E. L. Deci. “Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions.” *Contemporary Educational Psychology*, 25 (2000), 54–67.
Serfling, M. “Firing Costs and Capital Structure Decisions: Firing Costs and Capital Structure Decisions.” *The Journal of Finance*, 71 (2016), 2239–2286.
Shu, T., X. Tian, and X. Zhan. “Patent Quality, Firm Value, and Investor Underreaction: Evidence from Patent Examiner Busyness.” *Journal of Financial Economics*, 143 (2022), 1043–1069.
Stouffer, S. A. “Social Research to Test Ideas: Selected Writings of Samuel A. Stouffer.” New York: Free Press.
Stouffer, S. A., E. A. Suchman, L. C. DeVinney, S. A. Star, and R. M. Jr. Williams. “The American Soldier: Adjustment to Army Life.” Princeton, NJ: Princeton University Press.
Stouffer, S. A., A. A. Lumsdaine, M. H. Lumsdaine, R. M. Jr. Williams, M. B. Smith, I. L. Janis, S. Star, and L. S. J. Cottrell. “The American Soldier: Combat and Its Aftermath.” Princeton, NJ: Princeton University Press.
Tabor, S. R. “Assisting the Poor with Cash: Design and Implementation of Social Transfer Programs.” Washington, DC: World Bank.
Vandello, J. A., and D. Cohen. “Patterns of Individualism and Collectivism across the United States.” *Journal of Personality and Social Psychology*, 77 (1999), 279–292.

Wang, F., S. Xu, J. Sun, and C. P. Cullinan. “Corporate Tax Avoidance: A Literature Review and Research Agenda.” *Journal of Economic Surveys*, 34 (2020), 793–811.
Yitzhaki, S. “Relative Deprivation and the Gini Coefficient.” *The Quarterly Journal of Economics*, 93 (1979), 321–324.