The Clash of Spirituality and Strategy:
Exploring the Influence of Religiosity on AI Initiatives

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Abstract

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Keywords: Religiosity, Artificial intelligence, Risk-Aversion

JEL Classification: D22, D83, G30, O33

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Abstract

This study investigates the relationship between regional religious affiliations and corporate artificial intelligence (AI) application initiatives. We measure AI application initiatives in U.S. firms based on the disclosure of AI adoption terms in the business description section of their 10-K filings. Using a sample of U.S. public firms, we find that firms headquartered in more religiously affiliated counties are associated with lower levels of AI adoption. The results remain robust after addressing endogeneity concerns and conducting additional robustness checks. Further analyses of the channels through which religiosity discourages corporate AI application show that the lower likelihood of AI adoption in more religious areas is linked to fewer AI patents, less financial commitment to innovation, fewer inventor collaborations, and more conservative managerial risk-taking incentives.

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1. Introduction

The proliferation of artificial intelligence (AI) technology in recent years has exhibited remarkable progress, surpassing industry demarcations and establishing itself as a catalyst for profound change in production and management across diverse sectors (Agrawal et al., 2019; Crafts, 2021). In the global arena, countries are actively implementing strategic measures to enhance their competitive advantage in the field of artificial intelligence (AI) development. This is evident through various initiatives such as *The National Artificial Intelligence Research and Development Strategic Plan* by the U.S. government[1], and the European Union's *Communication on Artificial Intelligence for Europe*[2]. These initiatives reflect the commitment of nations to prioritize AI research and development in order to secure their position in the global AI landscape.

To date, the majority of existing studies on AI development have primarily concentrated on national or regional perspectives, with limited empirical evidence at the firm level (Venturini, 2022; Parteka and Kordalska, 2023). Given the growing academic recognition of AI's diverse impacts on businesses and the increasing focus on scrutinizing its effects at the firm level (Raj and Seamans, 2018), there remains a notable gap in research addressing the specific concerns that corporations may have when it comes to adopting and integrating AI technology.

Previous studies (Sheng et al., 2008; Luo et al., 2010) have highlighted that the acceptance of artificial intelligence (AI) is highly dependent on its contextual application. In today's business environment, a significant number of organizations, particularly in industries like finance, have either initiated or implemented AI-driven initiatives. However, one of the critical challenges in the widespread adoption of AI lies in the absence of standardized metrics to assess the overall

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[1] Available at: https://www.whitehouse.gov/wp-content/uploads/2023/05/National-Artificial-Intelligence-Research-and-Development-Strategic-Plan-2023-Update.pdf
[2] Available at: https://digital-strategy.ec.europa.eu/en/library/communication-artificial-intelligence-europe

reliability and credibility of AI applications. According to current regulatory frameworks, AI applications, especially those with high-risk profiles and based on machine learning techniques, must demonstrate "trustworthiness" and comply with mandatory criteria such as Sustainability and Fairness. Despite this, a universally accepted set of evaluation metrics for AI applications, particularly in the financial sector, has yet to be established (Giudici & Raffinetti, 2023).

The emergence of artificial intelligence (AI) has led to the development of a conflict theory, which suggests that the acceptance and attention given to AI by individuals can vary significantly. This variation is driven by a spectrum of perceptions, ranging from recognition of its potential benefits and utility to concerns over issues like loss of autonomy and potential security breaches (Dutton et al., 1987; Janssen et al., 2019; Milano et al., 2020; Nath and Sahu, 2020). The adoption of AI is a complex, dual-faceted issue, involving both positive and negative heuristics. This dichotomy influences people's attitudes towards AI, creating challenges in its practical implementation and posing a series of difficult problems that must be navigated (Złotowski et al., 2017; Sundar, 2020).

Our study investigates the complex relationship between community religiosity and corporate engagement with artificial intelligence (AI). We hypothesize that firms located in U.S. counties with higher levels of religiosity are less likely to adopt AI technology. Through an analysis of U.S. public firms, we find a significant inverse relationship between the level of religiosity in a firm's surrounding community and the firm's adoption of AI. The results are economically substantial, with a one-standard-deviation increase in community religiosity corresponding to an 11% decrease in the level of AI adoption. To address potential endogeneity issues, we implement an instrumental variable (IV) approach. Specifically, we use the lagged total population of the region as an instrument for community religiosity in humanistic attributes. This method strengthens the causal interpretation of our findings, confirming a causal relationship between community religiosity and firms' willingness to adopt AI technology.

Furthermore, we investigate the potential channels through which regional religiosity may hinder firms' willingness to adopt AI technology. We focus on two key channels: the *innovation commitment channel* and the *behavior channel*. We argue that the prevalence and potential consequences of artificial intelligence (AI) in the context of corporate innovation are crucial. The integration of AI into areas such as patents, trademarks, and scientific publications highlights its significant impact on innovation (Dernis et al., 2019). A lack of commitment to innovation may therefore hinder the adoption of AI. To explore this, we examine the effect of local religiosity on both innovation inputs (such as R&D expenses) and innovation outputs (such as AI patent activities) in U.S. firms. Our analysis shows a significant negative relationship between religiosity and corporate innovation, with more religious regions exhibiting lower levels of both innovation input and output. Additionally, these regions tend to have lower ratings for regional innovation performance. These findings strongly support the *innovation commitment channel*, indicating that higher religiosity in a community may reduce a firm's inclination to pursue AI-driven innovation. We also explore the *behavior channel*, focusing on two factors: inventor mobility and managerial risk-taking incentives. *Inventor Mobility*: The development of cutting-edge AI technology requires skilled human capital, particularly inventors, who may be less inclined to relocate to more religious and conservative areas. Inventors, like other professionals, are influenced by the living conditions of the regions they choose to settle in. Our empirical analysis shows that inventors prefer to move to more liberal areas rather than religiously conservative ones, which can negatively affect innovation output in more religious regions (Gao et al., 2020; Gu et al., 2022). This suggests that regional religiosity may hinder the attraction of top talent necessary for AI innovation. *Managerial*

Risk-Taking Incentives: Religious conservatism is often associated with higher levels of risk aversion (Shu et al., 2012; Adhikari and Agrawal, 2016; Gao et al., 2017; Chircop et al., 2020; Cebula and Rossi, 2021), whereas corporate innovation and the adoption of AI require managers to take higher risks (Mao and Zhang, 2018). Our findings show that managers in more religious areas exhibit significantly lower levels of risk-taking incentives, making them less willing to adopt AI technologies. This supports the behavior channel, suggesting that regional religiosity leads to a more risk-averse managerial culture, which in turn hinders the adoption of AI. Taken together, the evidence from both channels supports the idea that regional religiosity influences firms' willingness to adopt AI through both innovation commitment and behavioral factors.

To further underscore the significance of our research findings, we conduct an additional analysis to examine whether a company's adoption of Artificial Intelligence (AI) translates into tangible benefits at the firm level, particularly in terms of superior financial performance. We evaluate the firm-level performance using three well-established financial metrics: Buy-and-Hold abnormal returns (*BHAR*), Tobin's q (*Tobin q*), and Return on Equity (*ROE*). Our analysis reveals a positive relationship between a company's focus on AI adoption and its financial performance across these three metrics. Specifically, firms that have integrated AI into their operations tend to outperform their peers in terms of stock returns, firm valuation, and profitability. These findings highlight that AI adoption is not merely a technological trend but a key driver of enhanced financial outcomes, offering further support for the business case of adopting AI technology. This analysis strengthens our argument that AI adoption can lead to tangible firm-level benefits, contributing to both improved market performance and increased profitability.

To ensure the robustness of our empirical findings regarding the relationship between community religiosity and firm-level AI adoption, we conduct a battery of robustness tests. First, we extend the model to incorporate firm-level fixed effects along with year fixed effects to address potential omitted time-invariant, firm-specific characteristics. Second, it is worth noting that we use the fixed effects Poisson model to perform our main empirical analysis given the fact that the previous common approach of estimating a linear regression using the natural logarithm of one plus the count variable can be problematic and suffer from estimation bias (Cohn et al., 2022). Nevertheless, we also employ the log-transformed value of AI (1 plus the natural logarithm of AI application terms) as a robustness check. Third, we utilize an alternative proxy of AI adoption proxied by Babina et al. (2024), which emphasizes the portion of a firm's personnel possessing AI-related skills. This proxy provides an additional viewpoint on AI adoption by assessing a firm's human capital aspect, particularly the availability and deployment of individuals with AI expertise. The results from those robustness tests are consistent with our baseline findings. In each case, we continue to observe a negative relationship between community religiosity and AI adoption by local firms. These robustness tests reinforce our original conclusion, strengthening the evidence that firms headquartered in areas with higher levels of religiosity tend to exhibit lower levels of AI adoption.

Our study contributes to the existing literature in two folds. First, a rapidly growing body of research has focused on the interplay between emerging AI technology and capital markets. For instance, several studies have documented the positive effects of AI automation on managerial decisions and corporate performance. Specifically, these studies indicate that adopting AI can mitigate corporate exposure to systematic risks (Zhang, 2019), boost corporate sales and product innovation (Babina et al., 2024), generate an additional annual return premium (Knesl, 2023), and enable firms to adopt an aggressive liquidity policy by holding lower levels of precautionary cash reserves (Bates et al., 2024). Unlike these studies that highlight the benefits of AI utilization, our focus is on the factors that may potentially impede the development and adoption of AI technology. In particular, our findings pioneer the exploration of how religiosity influences corporate attitudes and actions toward AI adoption. By delving into this underexplored area, we provide valuable insights into the often-overlooked role of religious beliefs in shaping corporate responses to technological advancements. Second, another body of research documents the various influences of local religiosity on capital market activities. Prior studies suggest a positive link between religiosity and increased risk aversion, such as reduced default rates and cost of debt (Adhikari and Agrawal, 2016; Chen et al., 2016; Cai and Shi, 2019), lower risk-taking incentives for corporate managers (Cebula and Rossi, 2021), and more conservative investment strategies for hedge funds (Gao et al., 2017), mutual funds (Shu et al., 2012), and venture capitalists (Chircop et al., 2020). However, it is unclear how the conservatism induced by religiosity affects the adoption of new technologies, such as AI, at the firm level. Our research bridges the gap between the literature on religion and technology adoption. While studies on technology adoption are abundant, few have explored the intersection of religiosity and AI adoption in corporate settings. By synthesizing insights from both domains, we offer a nuanced understanding of how cultural and social factors intersect with technological advancements. This enriches scholarly discourse on the complex relationship between religion and modern innovation and has practical implications for policymakers, organizational leaders, and researchers.

The remainder of this paper is structured as follows: Section 2 reviews existing literature and develops our hypothesis; Section 3 presents our data, sample, and methodology; Section 4 documents the empirical analysis; Section 5 delineates the channel analyses; Section 6 elucidates our further analysis; and, finally, Section 5 concludes.

2. Literature review and hypothesis development

In recent years, Artificial Intelligence (AI) has undergone a notable transformation, evolving from a technology with potential into a significant and influential force within the technological landscape of the current decade (Hilpisch, 2020). The integration of AI has been widely adopted by businesses across various industries, with the primary objective of optimizing operational efficiency and effectiveness. Multinational corporations, including Facebook, Google, IBM, and Microsoft, have demonstrated a noteworthy commitment to allocating significant resources toward the field of AI. These corporations have astutely recognized the inherent capacity of AI to enhance and optimize their operational processes (Mhlanga, 2020). A considerable proportion of enterprises are currently engaged in the experimentation or implementation of AI technologies, as well as the integration of AI strategies into their operational frameworks. The rapid progress in computational information processing capabilities, coupled with the emergence of big data analytics technologies, has significantly enhanced the potential of AI to address complex tasks once considered beyond the reach of cognitive abilities (Mahroof, 2019). These advancements have laid the groundwork for AI to revolutionize decision-making procedures across various sectors (Aaldering & Song, 2020).

The growing enthusiasm surrounding artificial intelligence (AI) applications is evident in their widespread adoption across diverse industries. This trend signifies a fundamental transformation in corporate operations and strategic decision-making (Dwivedi et al., 2021). The exponential growth and seamless integration of AI highlight its profound capacity for transformation across various sectors, positioning it as a pivotal catalyst for innovation and operational excellence within the modern business environment.

The prominence of artificial intelligence (AI) in corporate decision-making processes has generated considerable interest and scrutiny. AI is perceived as a powerful tool with the potential to uncover hidden insights from data in a timely manner, thereby enhancing decision-making, knowledge management, and automating customer interactions within corporate settings (Brock and von Wangenheim, 2019; Jovanovic et al., 2021). As firms increasingly integrate advanced technologies such as AI across diverse sectors and roles, the demand for AI skills continues to rise (Alekseeva et al., 2021). According to Wilson and Daugherty (2018), there is a promising opportunity to augment employees' analytical acumen and decision-making abilities, while also cultivating a climate that fosters creativity within corporate teams.

The utilization of artificial intelligence (AI) in decision-making processes has been associated with several notable advantages, including increased effectiveness, accuracy, and flexibility. These benefits have been recognized by various scholars and industry experts, as evidenced by the works of Agrawal et al. (2017), Duan et al. (2019), and Metcalf et al. (2019). The successful realization of the potential advantages stemming from the symbiotic relationship between humans and AI is contingent upon the endorsement of AI technology by human decision-makers (Mathieson, 1991; Edwards et al., 2000).

Notwithstanding these perceived advantages, apprehensions regarding the potential adverse consequences of AI persist (Dreyfus and Hubert, 1992; Breward et al., 2017). Concerns have been raised regarding the potential for artificial intelligence (AI) to exhibit uncontrolled behavior, thereby leading to significant adverse societal outcomes (Johnson and Verdicchio, 2017). At the corporate level, the potential negative implications of artificial intelligence (AI) have become a topic of significant concern. These concerns have been acknowledged by authoritative bodies such as the European Commission and have also been highlighted in scholarly research conducted by Dwivedi et al. (2021)[3]. At an individual level, concerns regarding potential job displacement or the phenomenon commonly referred to as "technological unemployment" contribute to the anxieties experienced by both managers and workers (Jarrahi, 2018; Ransbotham et al., 2018). The deployment of AI technologies on a global scale threatens to automate entire categories of work, displacing manual labor and potentially leading to widespread unemployment and social disruption (Nourbakhsh & Keating, 2020). Moreover, AI has now reached a stage where it can match or even surpass human performance in many cognitive tasks (Nowak et al., 2018). The risk level associated with AI is difficult to accurately estimate due to the versatility and often unpredictable applications of General-Purpose AI (GPAI) (Novelli et al., 2023). The level of individuals' inclination to engage in collaborative efforts with machines remains uncertain, thereby underscoring the need for a more comprehensive comprehension of the conditions that facilitate cooperation between humans and artificial intelligence (AI) (Haesevoets et al., 2021).

The technology acceptance model posits that the decision to adopt or reject a new technology is influenced by several factors, one of which is the perceived usefulness of the technology by employees (Davis, 1989). The increasing impact of artificial intelligence (AI) has sparked discussions surrounding its integration with the human workforce, highlighting concerns about potential job displacement due to technological advancements (Winick, 2018). There are several obstacles to the widespread acceptance of AI within the workforce, both among employees and management. These barriers primarily revolve around concerns related to costs, uncertainties, and job security (Aisyah et al., 2017). The integration of AI into daily business operations is often hindered by employee resistance stemming from concerns about job security and a perceived lack

[3] Communication Artificial Intelligence for Europe. Available at: https://digital-strategy.ec.europa.eu/en/library/communication-artificial-intelligence-europe

of preparedness (Aisyah et al., 2017). Additionally, the current shortage of skilled labor exacerbates apprehensions about job displacement (James et al., 2017). Negative sentiments toward AI can be attributed to employees' fears of technological substitution leading to job loss (Winick, 2018). Furthermore, such negative sentiments can hinder successful collaboration with external partners in technology development, often resulting in a preference for internal initiatives, as evidenced by studies conducted by Katz and Allen (1982) and Lichtenthaler and Ernst (2006).

An exploration of the adoption of artificial intelligence (AI) among various demographic groups highlights the importance of cultural influences. The role of cultural nuances in shaping perceptions and the adoption of AI technology across different societal segments is significant. Understanding how cultural perceptions impact AI adoption requires a comprehensive examination of diverse social contexts to accurately assess individuals' attitudes toward AI (Bozdag & van den Hoven, 2015). Zhang (2020) emphasizes the profound interconnectedness between religion and science, shedding light on the dialectical thinking and logical deduction that are deeply ingrained in religious practices. He asserts that the impact of religion on scientific advancement varies, depending on the diverse aims and objectives pursued by humanity.

Indeed, prior studies in corporate finance have demonstrated the influence of religion on various corporate activities. For instance, firms with higher exposure to AI technologies like ChatGPT have shown higher excess returns on a daily basis compared to less exposed firms, suggesting that investors perceive AI adoption as a positive development (Eisfeldt et al., 2023). Additionally, investing in AI has been shown to enhance audit quality, reduce fees, and even displace human auditors, illustrating the profound impact of AI on traditional business processes (Fedyk et al., 2022). The transition to digital activities also leads to improved valuations, further supporting the notion that digitalization positively affects financial metrics such as earnings and sales (Chen & Srinivasan, 2023). Moreover, the potential to automate the workforce enhances a firm's operating flexibility, underscoring the operational benefits of adopting advanced technologies (Bates et al., 2024).

However, individuals in more religious areas tend to be more conservative toward new and risky ventures. Prior studies have revealed the negative influence of religiosity on corporate innovation. According to Gaskins et al. (2013), religious individuals tend to be more socially conservative compared to the general population. This suggests that religious beliefs are, to some extent, associated with resistance to change and novelty. Roccas (2005) further supports this viewpoint by pointing out that devout religious believers often place a high value on maintaining stability and avoiding uncertainty. This implies that for religious individuals, preserving the status quo and avoiding change may be a more attractive choice.

Companies in areas with more pronounced religious sentiment tend to display reduced levels of risk-taking, primarily due to two factors: heightened aversion to risk and adherence to ethical principles. Adhikari and Agrawal (2016) argue that these characteristics lead to reduced default rates, which in turn result in lower interest rates requested by banks. Gao et al. (2017) and Cebula and Rossi (2021) emphasize the cautious investment strategies adopted by companies in religiously inclined regions, suggesting a prevailing pattern of decreased vulnerability to risks. According to Chen et al. (2016), religiosity should be regarded as a significant country-level component, along with other institutional variables, that influences a nation's debt costs and capitalist growth. They argue that religiosity serves as an important source of societal norms and values. Additional empirical data from Shu et al. (2012), Chircop et al. (2020), and Cebula and Rossi (2021) further corroborates this claim, demonstrating that religion not only affects enterprises' investment choices but also influences their overall financial decisions.

Anecdotal evidence suggests that religious individuals often exhibit skepticism toward AI. This skepticism is exemplified by statements from prominent religious scholars and leaders. Professor Stang of Harvard Divinity School openly questions the intelligence of AI, stating, "I still remain skeptical that AI is quote-unquote intelligent." This sentiment is echoed by faith leaders and religious scholars who advise AI users to maintain a healthy dose of skepticism regarding the technology's capabilities. The Vatican's 2020 announcement of the Rome Call for AI Ethics underscores the Catholic Church's cautious approach, advocating for ethical considerations in AI development. Additionally, Matthew Ichihashi Potts points out that even if AI becomes more advanced and human-like, it cannot resolve existential questions in the way religion has throughout history. Surveys further illustrate this skepticism among religious communities. A Barna survey found that only 28% of Christians were hopeful about AI development, compared to 39% of non-Christians. When considering the widespread use of AI-enhanced robotic exoskeletons, 48% of highly religious Americans felt it was "meddling with nature" and a line that should not be crossed, whereas 78% of adults with low religious commitment viewed it positively. Black Protestants and White evangelical Protestants, in particular, expressed significant reservations, with 55% and 47%, respectively, viewing such technology as crossing an ethical boundary.

Existing literature highlights a broader trend of religious skepticism toward AI, driven by ethical concerns and fundamental differences in worldviews. Given these patterns, it is reasonable to expect that religiosity hinders AI adoption, as the inherent risk aversion in religious communities leads to resistance against integrating AI into various aspects of life and business. Thus, we postulate that a firm's focus on artificial intelligence (AI) would decline in instances where the level of religiosity within the geographic location of the company's headquarters is elevated. We therefore develop our hypothesis as follows:

Firms headquartered in areas with higher levels of religiosity exhibit lower levels of AI application initiatives compared to their counterparts.

3. Research design

3.1. Data and sample

To construct the sample for this study, we focus on U.S. public firms between the years 2005 and 2018. The key variable for measuring religiosity is the proportion of individuals in a specific county who self-identify as religious. This data is sourced from the American Religion Data Archive (ARDA), which provides extensive survey data on religious beliefs and practices across the United States. For AI utilization, we proxy the level of adoption by counting the number of times AI-related terms appear in the business description section of corporate 10-K filings. These filings provide an insight into how firms disclose their use and application of artificial intelligence technology in their operations. To link county-level data to firm headquarters, we use the Federal Information Processing Standards (FIPS) codes. These codes allow us to match firms to their respective counties based on geographic location. Additionally, to capture the social environment and factors that may influence corporate behavior, we use the social capital index, which is sourced from the Northeast Regional Centre for Rural Development (NRCRD) for each county. Economic and demographic characteristics at both the county and state levels are obtained from two reputable sources: the Bureau of Economic Analysis (BEA) and the United States Census Bureau. These datasets provide valuable insights into the local economic environment and population profiles that may influence firm behavior. Firm-specific characteristics are sourced from *Compustat*, a comprehensive database of financial, operational, and market data on U.S. firms. These characteristics allow us to control for factors that may affect AI adoption independently of the region's religiosity. The final dataset used in this study consists of 15,341 firm-year observations from 1,880 U.S. firms over the period from 2005 to 2018. This dataset enables a robust analysis of the relationship between community religiosity and AI adoption by firms, controlling for various firm and regional factors.

3.2. Variable construction

3.2.1. Dependent variable

The main dependent variable of this study is AI, which is a count variable for the total number of AI application related terms in corporate 10-Ks. We also use the variable of the natural logarithm of one plus the total number of AI terms, *Ln (1+AI)*, as an alternative measure in our robustness tests.

3.2.2. Independent variable

Scholars in existing literature have defined religiosity in various fashion. Prior studies by Hilary and Hui (2009), Shu, Sulaeman, and Yeung (2012), and Callen and Fang (2015) have significantly contributed to elucidating this intricate concept. Within the scope of this study, our explanatory variable, religiosity (*REL*), is construed as the percentage of individuals who is identified as adherents of a religious faith within the populace of a given county. A person is identified as having a religious belief if the person belongs to one of the religious groups with a congregation in the United States, including Evangelical Protestant, Black Protestant, Mainline Protestant, Orthodox, Catholic and other. The American Religion Data Archive (ARDA) meticulously collated survey data concerning religious adherence at the county level spanning the decades of 1980, 1990, 2000, and 2010, encapsulated within the comprehensive "Churches and Church Membership" files. These compiled files encapsulate invaluable insights into the evolving religious trends and observances prevalent within the United States.

3.2.3. Control variables

In line with previous study pertaining to the impact of religion on corporate business activities, we control for a vector of firm specific characteristics, including *Sales_Growth*, *ROA*, *Firm_Size*, *Firm_Age*, *Leverage*, *Cash_Ratio*, *M/B*, *Female_Director_Ratio,* and Herfindahl-Hirschman Index (*HHI*). *Sales_Growth* is measured by the natural logarithm of the percentage increase in total sales, while *ROA* is calculated as net profit (earnings before interests, taxes, depreciation, and amortization) scaled by total assets. *Firm_Size* is calculated as the natural logarithms of the book value of total assets and *Firm_Age* is determined by and the natural logarithms of one plus the number of years that the firm has been recorded in *Compustat*. *Leverage* is defined as long-term debt plus current liabilities, scaled by the book value of total assets. *Cash_Ratio* represents the ratio of cash and other equivalents to current liabilities, whereas *M/B* is the market value of equity to the book value of equity. *Female_Director_Ratio* is the ratio of female directors to the total number of board directors. *HHI* reflects the market competitiveness of a firm's industry, which is calculated as the sum of the squared market share of the total sales of each firm in a 3-digit standard industrial classification (SIC) industry of a fiscal year. In addition, we control for a demographic factor at the county-level, *Population_Growth*, which is the percentage of the county population growth rate, sourced from the United States Census Bureau. All continuous variables are winsorized at the 1st and the 99th percentiles to eliminate the influence of outliers. The details of variable definitions are presented in Appendix A.

3.3. Methodology

To empirically investigate our research question pertaining to the impact of religiosity on utilizing the technology of artificial intelligence, we use the fixed effects Poisson model as the baseline specification. We chose to employ the Poisson model because the previous common approach of estimating a linear regression using the natural logarithm of one plus the count variable can be problematic and suffer from estimation bias (Cohn et al., 2022). Therefore, the fixed effects Poisson model is recommended when the dependent variable is a count variable (e.g., Correia et al., 2020; Cohn et al., 2022). Specifically, the econometric equation is defined as follows:

$$AI = \alpha + \beta_1 REL + \sum\delta Controls + \lambda_k + \lambda_t + \varepsilon \qquad (1)$$

whereas *AI* stands for the number of times a firm mentions adopting AI in the 10-K reports. The primary variable of interest, *REL*, represents the estimated fraction of religious practices within the community of a firm at the county-level in a given year. *Controls* represents a vector that includes all of the control variables. All control variables are as of the end of the prior year. λ_k and λ_t represent industry and year fixed effects, respectively. The classification of industries is determined by the two-digit Standard Industrial Classification (SIC) codes. According to our hypothesis, the coefficient (β_1) on communal religiosity is negative and statistically significant.

4. Empirical results

4.1. Summary statistics

Table 1 presents the descriptive statistics of the primary variables. The mean value of *AI* is 0.07, which suggests that approximately 7% of the firm-year observations exhibit the AI-related terms in corporate 10-K filings. Pertaining to our main explanatory variable, *REL*, the mean value is 0.55, indicating almost half of the population of U.S. counties are religious. Before moving on to our multivariate regression analysis, we check the correlation matrix for all independent variables of all firms in our sample (see Table 2). No statistical evidence in Table 2 suggests the concern of multicollinearity in our subsequent regression analysis[4].

[4] In our unreported analysis, we also check the variance inflation factors (VIFs) in our main regression model. The mean and maximum VIF values are well below the critical value of 10 (Kutner et al., 2005), which reveal no evidence of multicollinearity.

[Please Insert Table 1 and 2 about here]

4.2. The effect of community religiosity on corporate AI utilization

Table 3 presents the multivariate baseline regression analysis on the effect of community religiosity on the firm's application on AI. The dependent variables in columns (1), (2), and (3) are all *AI*, which represents the total count of all AI-related terms in firms' 10-K reports. Column (1) presents the results from the Poisson model without adding control variables and different fixed effects. Column (2) does not contain the control variables but includes year and industry fixed-effects, while Column (3) further adds the control variables along with the fixed effects. As expected, all the coefficients on *REL* are negative and highly statistically significant ($p < 0.01$), suggesting that firms headquartered in more religious counties are less likely to utilize the cutting-edge AI technology. The results are economically meaningful. For example, Column (3) indicates that, on average, a one-standard-deviation increase in *REL* corresponds to a 11% decrease in the firm's AI application tendency.

[Please Insert Table 3 about here]

4.3. Endogeneity concern

The above empirical evidence illustrates that firms in counties with higher levels of religious population are quite conservative toward the AI technology. It is, however, important to examine the direction of the causality between religiosity and corporate willingness of adopting AI. Our empirical results could be driven by other factors omitted in our analysis and related to both religiosity and corporate AI application. To address the above endogeneity concerns, we select an instrumental variable (IV) related to community religiosity but exogenous to corporate enthusiasm to AI. Following Hilary and Hui (2009), we employ the lagged population ($Population_{lagged}$) at the county-level as the instrument variable (IV). Specifically, since our proxy of religiosity, REL, is collected every ten years, we use a county's population with a ten-year lag as our IV. The instrument must satisfy two specific criteria, the relevance condition and the exclusive restriction. The relevance condition necessitates that the IV is related with the endogenous variable. The possible impact of past population expansion may influence the portion of religious population within a specific area. In areas experiencing rapid population growth, it is likely to see a corresponding increase in the influx of people practicing various religions. As a result, this tendency leads to significant changes in both the extent and ratio of religious variety in those locations. Thus, we believe our IV satisfies the relevance condition. Pertaining to the exclusive restriction, it is very unlikely that the population ten years ago in a county would have an impact on AI application tendency of the firms currently located in this county. Thus, this IV is supposed to satisfy the exclusive restriction.

The results of the two-stage IV analysis are presented in Table 4. In Column (1), the coefficient of our IV, is positive and highly significant (p-value <0.01), which represents a strong correlation between the local historical population and the level of local religious beliefs, indicating that the IV satisfy the relevance condition. Meanwhile, the statistically significant Stock-Yogo test (Stock and Yogo, 2005) further confirms that our IV is not a weak instrument. In the first stage regression, the coefficient of *Population_lagged* on REL is positive and statistically significant ($p < 0.01$), suggesting a positive link between a county's overall population in the past and the level of religiosity. The result of the second-stage regression is shown in Column (2), the coefficient of the fitted value of *REL* is still negative and significant (p-value <0.01). Hence, we conclude that after addressing the endogeneity issue, the results of our IV analysis confirm our baseline results. Firms located in more religious counties exhibit less enthusiasm toward the cutting-edge AI technology, in comparison with their counterparts.

[Please Insert Table 4 about here]

5. Potential mechanisms

We realize that religiosity, as a complex social and cultural phenomenon, may not have a straightforward impact on corporate focus on AI application. On the contrary, this influence is often indirectly reflected through a series of channels. Therefore, to better delve into the analysis of the association between religiosity and corporate AI utilization tendency, we need to identify and explore these possible channels through which community religiosity in a county hinders the enthusiasm toward AI amidst the firms located in this county.

Among numerous potential mechanisms, we choose corporate innovation, regional innovativeness, and corporate financial commitment on innovation as our primary focus. In addition, we identify two behavior channels to explain the negative impact of religiosity on firms' AI focus, inventor mobility and corporate risk-taking tendency respectively.

5.1. Innovation commitment channel

5.1.1. Corporate AI-related innovation

We know that AI is one of the most advanced technology currently and itself is considered the outcome of innovation. Meanwhile, the development of AI needs to be fueled by continuous patenting activities on AI. Babina et al (2024) also show that firms investing in AI technologies are meanwhile associated significant growth on corporate patenting activities. Bénabou, Ticchi, and Vindigni (2015) discover a strong negative correlation between religion and the number of patents per capita. Their analysis shows that religiosity is consistently associated with lower openness to new ideas and risk-taking, two critical drivers of patenting activity. In regions where religiosity is higher, individuals and businesses may be more risk-averse, less willing to pursue innovative projects, and more likely to focus on maintaining established practices rather than exploring new technological frontiers. This could hinder the overall level of entrepreneurial activity and reduce the number of AI-related patents filed, as religiously conservative environments may discourage experimentation and creativity, which are essential for innovation. Therefore, we test the innovation channel to see whether there is a negative link between AI-related patenting activities and community religiosity. Patents have traditionally been utilized as a measure of a company's level of innovation and technological prowess (e.g., Lanjouw et al., 1998; Hall et al., 2001 and 2005; Bernstein, 2015; Kogan et al., 2017). We obtain data on corporate AI-related patenting activities from the United States Patent and Trademark Office (USPTO). Specifically, the proxy is constructed as the number of granted AI-related patents in a given year amidst U.S. firms.

To test this innovation commitment mechanism, we employ the fixed effect Poisson model given the fact that our dependent variable, number of granted AI-related patents, is a count variable. Our variable of interest remains the *REL*. The results of the corporate innovation mechanism are presented in Column (1), Table 5. The coefficient of *REL* is negative and statistically significant (p-value <0.01). This finding further confirms that the negative impact of community religiosity on firms' AI focus may be caused by firms' overall innovation commitment.

5.1.2. Regional innovativeness:

Herrera and Nieto (2008) observe that firms located in central regions, which concentrate an important percentage of the national innovation activity, are more proactive in innovation than those located in peripheral regions. Turkina et al. (2019) find that firms are more likely to innovate when they are located in strong innovation clusters. If the region itself emphasizes innovation, then participating companies will have a greater willingness to innovate to obtain the pioneering technology as AI. Prior studies also suggest that there exists a negative relationship between religiosity levels and innovativeness among individuals (Bénabou et al., 2015). Additionally, studies have found that higher levels of religiosity are associated with reduced support for technological advancements (Brossard et al., 2009; Sherkat, 2011). Bénabou et al. (2015) have successfully established a robust and consistent association between heightened religiosity and less favorable attitudes towards innovation. The observed correlation implies that heightened levels of religiosity may potentially foster a prevailing sense of caution or doubt towards novel undertakings, thereby reducing the region's emphasis and investment in innovation. According to the above literature, a firm's passion toward AI could be driven by a region's innovation rates. Therefore, we investigate the second mechanism that whether religiosity tends to discourage a region's innovativeness. We use the innovation rating, the technology and science index of a U.S. state, as the measure of the regional innovativeness. The data on innovation rating is retrieved from the Milken Institute.

We report the results for the regional innovativeness channel in Column (2), Table 5. The results of the regression analysis indicate a statistically significant and negative coefficient for the variable *REL*, with a significance level of $p<0.01$, suggesting that regions with a heightened degree of religiosity are associated with diminished capacity for innovation. This finding substantiates the notion that community religiosity exhibits a negative influence on a region's innovation rating, which may lead to the conservatism toward AI.

5.1.3. Financial commitment on innovation

Brossard et al. (2009) conduct a comprehensive investigation, unearthing a noteworthy inverse relationship between religiosity and the inclination to allocate financial resources towards the advancement of technology in the first place. This finding implies a plausible hesitancy among individuals with religious affiliations to wholeheartedly embrace and endorse these technological advancements. If the conservatism associated with religious beliefs tend to negatively influence the financial commitment to technological innovation in the first place, firms in more religious areas are unlikely to exhibit enthusiasm toward the adoption of artificial intelligence.

We employ firms' investment on research and development (R&D) to gauge firms' financial commitment on innovation and report the related empirical results for the impact of religious affiliation proportion on corporate R&D spending in Column (3), Table 5. Consistent with our expectations, the regression analysis reveals a negative coefficient for the variable of interest, *REL*, which is statistically significant at 1% level. This finding implies that firms headquartered in communities with a higher religiosity level are inclined to allocate fewer financial resources towards advanced technology development, corroborating that the decrease in the corporate R&D spending, induced by community religiosity, leads to a drop in the level of utilizing AI.

[Please Insert Table 5 about here]

5.2. Behavior channel

5.2.1. Inventor mobility

Gao et al. (2020) and Gu et al. (2022) emphasize the substantial influence of inventor mobility on innovation. Implementing policies that cultivate healthier working conditions (smoking ban in workplace) may effectively recruit highly productive innovators and significantly boost the productivity of existing employees, therefore encouraging invention. In addition, when inventive individuals leave due to conservative ideological reasons (Gu et al., 2022), it has a detrimental impact on both the amount and the excellence of innovative outcomes. In line with the argument of Gu et al., (2022), innovators may be less willing to join firms in conservative communities characterized by a high degree of religious devotion, whereas prefer to work in areas with a diverse and liberal environment. Consequently, companies in religiously conservative areas may lack adequate innovators to focus on the development of AI technology. To quantify inventor mobility, we look into inventor comers (number of persons) to the firm in our sample. Specifically, we define inventors as persons who, with respect to a given year *t*, have generated at least one patent in the preceding year (year *t*-1) and will generate at least one patent in the following year (year *t*+1). The information on inventors' patenting activities is obtained from *Patent Network Dataverse*. Therefore, an inventor is considered an 'inventor comer' if s/he satisfies all the following criteria: s/he has a new engagement with firm *j* in year *t*; produced at least one patent in year *t*-1 with another firm (*k*); and produces at least one patent in firm *j* in year *t*+1.

The results pertaining to inventor mobility are presented in Column (1), Table 6. The Possion regression analysis reveals a negative coefficient for the variable *REL*, which is highly statistically significant ($p<0.01$). This finding suggests that firms in more religious communities are difficult to recruit inventors than those in less religious areas. Thus, the reduced mobility of inventors in highly religious communities brings obstacles for local firms to accept AI. Overall, this analysis confirms that the negative impact of community religiosity on inventor mobility significantly mediates the relationship between community religiosity and firms' enthusiasm on AI adoption.

5.2.2. Corporate risk-taking incentive

It is well recognized that the innovation projects are risky and have high likelihood of failure. Meanwhile, innovation requires the exploration of new as well as unverified methods (Holmstrom, 1989, Mao and Zhang, 2018). Artificial intelligence, a specific and complex type of innovation, is without exception. Thus, to fulfill corporate innovation activities, it requires high level of managerial risk-taking incentive. Specifically, Mao and Zhang (2018) document a positive link between corporate innovation commitment and managerial risk-taking incentive. Prior studies document that firms in more religious areas are associated with higher level of risk aversion (e.g., Chen et al., 2016; Gao et al, 2017; Cai & Shi, 2019; Cebula & Rossi, 2021). If firms more religious counties are associated with higher degree of risk aversion, managers in such firms may also have lower risk-taking incentive and therefore are less enthusiastic to AI application. In light of this situation, it is crucial to examine the potential impact of community religion on the risk-taking motivations of CEOs. To test this conjecture, we employ *VEGA* as the proxy of managerial risk-taking incentive. Following Coles et al. (2013), we define *VEGA* as the change in the dollar value of the CEO wealth for a 1% change in the annualized standard deviation of stock returns.

We report the results for the managerial risk-taking incentive in Column (2), Table 6. The regression analysis reveals a negative and statistically significant ($p<0.01$) coefficient for the variable *REL*. This finding implies that CEOs in firms headquartered in communities with a higher religiosity level are associated with lower risk-taking incentive and thereby tend to avoid risky activities such as AI application.

[Please Insert Table 6 about here]

6. Further analysis

6.1. Financial performance

In this section, we explore whether firm's enthusiasm on adopting AI technology can produce any tangible benefits to such firms. To answer this question, we conduct an additional analysis to see whether a company's disclosed AI application will translate into superior firm performance. We employ the following three primary metrics to evaluate firms' financial performance thereafter: *BHAR*, *Tobin q*, and *ROE* respectively (Lyon et. al, 1999, Singh et. al, 2018). Our variable of interest, *AI*, and all control variables are as of the end of the prior year.

The empirical results regarding financial performance are reported in Table 7. We report the influence of AI adoption on *BHAR*, *Tobin q*, as well as *ROE* in Column (1), (2), and (3) respectively. We can see clearly that the coefficients of *BHAR*, *Tobin q*, as well as *ROE* are all positive and statistically significant at 1% level. Our findings indicate that corporate AI utilization can generate significant pecuniary benefits for such firms. Therefore, the presence of a positive link between AI application and financial performance highlights the strategic significance of implementing AI technology to improve corporate effectiveness and competitiveness in the current dynamic business environment.

[Please Insert Table 7 about here]

6.2. Within firm fixed effects

To ensure the robustness of the baseline findings, we extend the model to incorporate firm-level fixed effects along with year fixed effects. The baseline specification addresses unobserved variation at the industry and year levels, while the incorporation of firm fixed effects considers potential omitted time-invariant, firm-specific aspects. This approach emphasizes intra-firm heterogeneity, documenting temporal variations in AI applications for the same entity.

Table 8 indicates that the coefficient for *REL* remains negative and statistically significant ($p < 0.01$), even after controlling for firm-level fixed effects. These findings confirm that differences across firms do not drive the negative association between community religiosity and corporate AI adoption. This evidence strengthens the argument that religiosity exerts a robust, consistent influence on firms' AI initiatives.

[Please Insert Table 8 about here]

6.3. Linear model estimation

So far, our regression analysis for corporate disclosed AI adoption is largely based on fixed effect Poisson model given that the proxy of AI initiatives is a count variable. Nonetheless, prior studies also use the logarithm transformed value of count variables to perform linear regression analysis. To further check whether the empirical results based on linear model are consistent with those estimated by Poisson model, we construct logarithm transformed value for *AI* and perform OLS regression analysis.

Table 9 presents the OLS regression analysis for the effect of community religiosity on corporate AI initiatives using *Ln (1+AI)*. Column (1) include industry and year fixed effects, whereas Column (2) include firm and year fixed effects. As expected, the coefficients on *REL* are negative and highly significant ($p < 0.01$). Overall, these results reinforce our main findings about the negative effect of community religiosity on the firm's eagerness of AI utilization.

[Please Insert Table 9 about here]

6.4. Alternative proxy of AI initiatives

In order to ensure the robustness of our empirical findings pertaining to the link between community religiosity and a firm's disclosed artificial intelligence adoption initiatives, we carry out a further robustness test. Specifically, we utilize the alternative metric of AI adoption employed by Babina et al. (2024), which emphasizes the percentage of a firm's personnel possessing AI-related skills. Babina et al. (2024) show that firms with more AI-skilled workers are associated with higher market value as well as more product innovation output. This proxy provides an additional viewpoint on AI adoption by assessing a firm's human capital aspect, particularly the availability and deployment of individuals with AI expertise. The dependent variable, *AI Employees*, is defined as the ratio of AI-skilled workers to total employees in a firm.

Table 11 displays the results, with Column (1) presenting estimates that include industry and year fixed effects, whereas Column (2) integrates firm and year fixed effects. In both specifications, the coefficients for *REL* are consistently negative and statistically significant ($p < 0.05$; $p < 0.01$). This finding further suggests that higher levels of community religiosity are associated with a lower proportion of AI-skilled employees within firms, corroborating our conclusion that religion serves as an impediment to the AI application initiatives.

[Please Insert Table 10 about here]

7. Conclusion

In this study, we comprehensively examine the complex interplay between community religiosity and the use of artificial intelligence (AI) in U.S. firms. Our investigation aims to shed light on the extent to which religious beliefs influence corporate applications of AI technologies. The analysis reveals a significant inverse correlation between firms located in religiously conservative areas and their level of engagement with cutting-edge AI technologies. To explore the mechanisms through which community religiosity negatively affects corporate AI adoption, we find that religious convictions impact corporate enthusiasm for AI by reducing patenting activities, lowering regional innovation ratings, and limiting financial commitments to innovation. Additionally, more religious areas are associated with fewer inventor relocations and lower managerial risk-taking incentives. Furthermore, our empirical analysis suggests that firms' AI applications tend to yield tangible financial benefits.

These insights are crucial for governments, organizations, and researchers seeking to understand the complex forces that shape corporate attitudes toward disruptive technologies like AI. We emphasize the need for a nuanced understanding of how local religious beliefs intersect with corporate goals regarding AI, clarifying the complex interaction between cultural ideals, religious affiliations, and technological advancements in corporate environments.

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Table 1. Summary statistics

This table presents the summary statistics for the variables used to measure the impact of religiosity at the county-level on AI application (including control variables). Our main sample consists of 15,341 firm-year observations during the period 2005 – 2018. We report the number of observations (N), the mean (Mean), the median (Median), the standard deviation (SD), the 25th percentile (P25), and the 75th percentile (P75) respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in the Appendix A.

Variables	N	Mean	Median	SD	P25	P75
AI	15,341	0.07	0.00	0.33	0.00	0.00
REL	15,341	0.55	0.55	0.12	0.46	0.63
Sales Growth	15,341	8.22	0.08	0.76	-0.02	0.25
ROA	15,341	0.08	0.03	0.07	0.03	0.12
Leverage	15,341	0.21	0.09	0.24	0.00	0.35
Firm Size	15,341	6.41	6.53	1.28	5.57	7.18
Firm Age	15,341	11.63	11.00	6.45	6.00	17.00
Cash Ratio	15,341	0.15	0.07	0.18	0.02	0.21
B/M	15,341	2.52	1.12	4.55	0.53	2.26
HHI	15,341	597.69	325.80	587.82	265.05	715.65
Female Director Ratio	15,341	0.12	0.11	0.11	0.00	0.20
Population Growth	15,341	6.37	40.30	2.09	5.00	7.83

Table 2. Correlation Matrix

This table reports the correlation matrix for the main variables. Variable definitions are provided in Table A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) AI	1											
(2) REL	-0.062	1										
(3) Sales Growth	-0.036	-0.003	1									
(4) ROA	0.148	-0.016	0.003	1								
(5) Leverage	0.037	-0.031	0.038	0.035	1							
(6) Firm Size	-0.046	-0.031	0.006	-0.12	-0.028	1						
(7) Firm Age	0.071	0.02	-0.131	0.025	-0.025	0.016	1					
(8) Cash Ratio	-0.164	0.052	0.096	-0.044	-0.278	0.048	-0.103	1				
(9) B/M	0.062	-0.055	-0.069	-0.02	0.017	0.028	-0.013	-0.25	1			
(10) HHI	0.084	-0.066	-0.046	0.056	0.056	-0.032	0.068	-0.129	-0.08	1		
(11) Female Director Ratio	0.014	-0.051	0.02	0.001	0.086	0.121	0.02	-0.051	0.04	0.014	1	
(12) Population Growth	-0.278	0.022	0.045	-0.01	0.018	-0.106	-0.086	0.031	-0.097	-0.026	0.056	1

Table 3. The effect of community religiosity on corporate AI application

This table presents the results of the fixed effect Poisson regression for the effect of community religiosity on firms' AI application. The dependent variable is *AI*, which represents the number of AI application terms in the business description section of 10-Ks. *REL* is the ratio of religious people in the population of the county in which a firm is headquartered. Column (1) presents the baseline result without any control variables and fixed effects. Column (2) includes year and industry effects. Industry classification is determined by the two-digit Standard Industrial Classification (SIC) codes. Column (3) adds all control variables and the fixed effects. Detailed variable definitions are presented in Appendix A. All control variables are as of the end of the prior year. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) ***AI***	(2) ***AI***	(3) ***AI***
REL	-0.204***	-0.112***	-0.111***
	(0.0223)	(0.0229)	(0.0241)
Sales Growth			-0.007*
			(0.0035)
ROA			0.035
			(0.0366)
Leverage			-0.001
			(0.0131)
Firm Size			-0.005**
			(0.0022)
Firm Age			0.001**
			(0.0004)
Cash Ratio			0.007
			(0.0182)
B/M			-0.001
			(0.0007)
HHI			0.011
			(0.0131)
Female Director Ratio			-0.105***
			(0.0261)
Population Growth			-0.000
			(0.0002)
Constant	0.181***	0.131***	0.070*
	(0.0125)	(0.0128)	(0.0377)
Year FE	No	Yes	Yes
Industry FE	No	Yes	Yes
Observations	15,341	15,341	15,341
R-squared	0.005	0.079	0.087

Table 4. Instrumental variable analysis

This table reports the results for the two-stage instrumental variable (IV) regression addressing the potential endogeneity issue of the presence of female board directors. Our IV is *Population_lagged*, which is the ten-year lagged population of a U.S. county. We take the predicted value of *REL* from the first stage regression analysis and include it in the second-stage estimation. Column (1) presents the results of the first stage estimation, whereas Column (2) reports the second-stage estimation. See Appendix A for detailed information for all variables. Year and industry fixed effects are included. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) First stage ***REL***	(2) Second stage ***AI***
$Population_{lagged}$	0.006***	
	(0.0007)	
$REL_{predicted}$		-0.933***
		(0.3546)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Stock-Yogo test	37.84***	
Observations	15,341	15,341
R-squared	0.215	0.019

Table 5. Religiosity and corporate innovation commitment

This table presents the results for the mechanism (*innovation commitment channel*) through which community religiosity hinders corporate AI utilization. We employ three proxies to test the innovation commitment mechanism, granted AI-related patents, regional innovation rating, as well as R&D expenditures respectively. The dependent variables in Columns (1) to (3) are *Patents*, *Innovation rating*, and *R&D*. Each column includes the same set of control variables as in Table 3. Detailed variable definitions are given in Appendix A. Year and industry fixed effects are included. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***AI Patents***	(2) ***Innovation Rating***	(3) ***R&D***
REL	-14.021***	-19.807***	-0.069***
	(2.6417)	(0.8801)	(0.0074)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	15,341	15,341	15,341
R-squared	0.112	0.324	0.586

Table 6. Religiosity and the behaviors of corporate managers and inventors

This table presents the results for the mechanism (*behaviors channel*) through which community religiosity hinders corporate AI utilization. We examine the behaviors of inventors (inventor mobility) as well as corporate managers (risk-taking incentive) respectively. The dependent variable in Column (1) is ***Inventor mobility***, whereas ***VEGA*** in Column (2). Each column includes the same set of control variables as in Table 3. Detailed variable definitions are given in Appendix A. Year and industry fixed effects are included. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***Inventor Mobility***	(2) ***VEGA***
REL	-3.937***	-89.320***
	(1.3991)	(27.7900)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	15,341	15,341
R-squared	0.089	0.266

Table 7. The effect of AI application on financial performance

This table presents the regression analysis for the effect of corporate AI application on firm's financial performance, measured by buy-and-hold returns, Tobin's q, and ROE. The dependent variables in Column (1), (2), and (3) are *BHAR*, *Tobin q*, and *ROE*, respectively. The variable of interest, *AI*, and all control variables are as of the end of the prior year. Each column includes the same set of control variables as in Table 3. Detailed variable definitions are given in Appendix A. Year and industry fixed effects are included. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***BHAR***	(2) ***Tobin q***	(3) ***ROE***
AI	0.023***	0.271***	0.001***
	(0.0083)	(0.0596)	(0.0004)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	15,341	15,341	15,341
R-squared	0.152	0.332	0.670

Table 8. Community religiosity on corporate AI application (within firm fixed effects)
This table presents the results of the Poisson fixed effects regression analysis for the effect of community religiosity on corporate AI application. The dependent variable, AI, is proxied by the number of AI application terms in the business description section of corporate 10-K reports. Unlike the baseline specification, which includes industry and year fixed effects, this model incorporates firm and year fixed effects. The same set of control variables as in Table 3 is included. Detailed variable definitions are provided in Appendix A. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***AI***
REL	-0.103***
	(0.0252)
Controls	Yes
Year FE	Yes
Firm FE	Yes
Observations	15,341
R-squared	0.654

Table 9. Community religiosity on corporate AI application (linear model)

This table presents the OLS regression analysis for the effect of community religiosity on corporate AI application. AI application is proxied with the natural logarithm of one plus the number of AI application terms in the business description section of corporate 10-K. The same set of control variables are included as in Table 3. Detailed variable definitions are given in Appendix A. Year and industry fixed effects are included in Column (1), whereas year and firm fixed effects are included in Column (2). Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Ln (1+AI)	***Ln (1+AI)***
REL	-0.064***	-0.079***
	(0.0140)	(0.0263)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	No	Yes
Industry FE	Yes	No
Observations	15,341	15,341
R-squared	0.085	0.601

Table 10. The effect of community religiosity on corporate AI application (alternative proxy)
This table presents the regression analysis for the effect of community religiosity on corporate AI application by utilizing an alternative AI proxy. Following Babina et al. (2024), AI application is gauged as the proportion of AI-skilled employees within a firm. The dependent variable, *AI Employees*, is defined as the ratio of AI-skilled employees to total employees. Column (1) includes industry and year fixed effects, while Column (2) incorporates firm and year fixed effects. The same set of control variables as in Table 3 is included. Detailed variable definitions are provided in Appendix A. Coefficient estimates are reported with standard errors in parentheses below, which are clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***AI Employees***	(2) ***AI Employees***
REL	-0.598**	-0.744***
	(0.2710)	(0.1230)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	15,341	15,341
R-squared	0.654	0.165

Appendix A. Variable Definitions

Variable	Definition	Source
AI	The total number of disclosed AI application terms in the business description section of 10-K filings	SEC EDGAR
AI Patents	The number of granted AI-related patents in a given year amidst U.S. firms	USPTO
AI Employees	The ratio of AI-skilled employees to total employees in a firm	Babina et al. (2024)
REL	The ratio of religious people in the population of the county in which a firm is headquartered.	American Religion Data Archive
Sales Growth	Natural logarithm of the percentage increase in annual total sales	Compustat
ROA	Net profit (earnings before interests, taxes, depreciation and amortization) scaled by total assets	Compustat
Leverage	Long-term debt plus current liabilities, scaled by the book value of total assets	Compustat
Firm Size	Natural logarithm of the book value of total assets	Compustat
Firm Age	Natural logarithm of one plus the number of years that a firm has been recorded in Compustat	Compustat
Cash Ratio	The ratio of cash and other equivalents to total assets	Compustat
M/B	Market value of equity to book value of equity	Compustat
HHI	Sum of the squared market share of each firm's total sales in a 3-digit standard industrial classification (SIC) industry	Compustat
Female Director Ratio	The ratio of female directors to the total number of board directors	BoardEx
Population Growth	Annual percentage growth of a county's population	United States Census Bureau
$Population_{lagged}$	The ten-year lagged population of a county	United States Census Bureau
Patents	The number of granted patents in a given year amidst U.S. firms	USPTO
Innovation Rating	The technology and science index of a U.S. state	Milken Institute
R&D	The maximum value of research and development expenses and zero, scaled by the book value of total assets	Compustat
Inventor Mobility	The number of inventors coming to a county. An inventor is a comer to firm j in year t if s/he generates at least one patent in another firm (k) in year t-1 and generates at least one patent in firm j in year t+1	Patent Network Dataverse (Harvard Dataverse)
VEGA	The change in the dollar value of the CEO wealth for a 1% change in the annualized standard deviation of stock returns at the end of the fiscal year	Dr. Lalitha Naveen's website (http://sites.temple.edu/lnaveen/data/)
BHAR	The buy-and-hold return of a firm less the buy-and-hold return of the CRSP equal-weighted index in a	CRSP

	given year	
Tobin q	Market value of assets divided by the book value of assets. Market value of assets is calculated as: total assets – book value of equity + market value of equity. Market value of equity is calculated by the number of common shares outstanding multiplies the share price	CRSP
ROE	Net income scaled by shareholder's total equity	Compustat