Measuring the Economic Impact of AI through Forward-Looking Firm Communications*

Jiacheng Liu†

Latest Version URL (Updated Regularly)

First Draft: June 2023
This Draft: December 2023

Abstract

I present a novel measure of the economic impact of AI using forward-looking managerial assessment contained in firm filings and earnings calls. I establish five new facts: (1) AI interest is rapidly growing among US firms, with significant cross-industry differences. (2) GPT annotations reveal that most of the firms view AI impact as moderately positive, with most of the expected economic impact on labor and investment. (3) AI is more likely to augment workers rather than displace workers. (4) AI-adopting firms are more efficient, profitable, and valued higher while having lower leverage and paying out less. (5) Non-creative knowledge tasks (e.g., Information recording) are more likely to be automated rather than augmented by AI. This paper contributes to measuring and understanding the economic interactions between AI and the business sector.

*Acknowledgments: I especially thank my advisor M. Deniz Yavuz for his invaluable advice. This paper would not have been possible without many insightful conversations with him. I would also like to thank Mara Faccio, Sergey Chernenko, Craig Brown, Peter G. Hansen, Ha Diep-Nguyen, and Kaushik Vasudevan for their helpful comments. First draft: June 1, 2022. All errors are my own.

†Purdue University, jiacheng-liu@purdue.edu. Comments welcome.

1 Introduction

Recently, there has been a leap in the capabilities of artificial intelligence (AI) (e.g., large language models (Thoppilan et al., 2022; OpenAI, 2023)). Given the projected trajectory of AI systems toward greater power and sophistication, it is imperative to measure and understand their potential economic implications. A growing literature has measured the economic impact of AI with a bottom-up approach: start with AI exposure at the task or worker level and aggregate up (e.g., Eloundou et al. (2023); Webb (2020); Felten et al. (2018); Brynjolfsson et al. (2018); Babina et al. (2024)). While this bottom-up approach excels at measuring the realized impact of AI, the forward-looking nature of firm communications motivates an alternative top-down approach: start from the firm and use GPT to go back down to the task level.

In this study, I directly measure the perceived future impact of AI on the business sector using firm filings and earnings calls. The business sector plays a vital role in the economy, contributing a substantial 72 percent to the GDP in the OECD economy (McKinsey, 2021). Therefore how firms adopt AI has the utmost importance in the economic impact of AI. Firm filings and earnings call transcripts are comprehensive documents providing information about managerial assessments and various aspects of firms' investments, and strategies, including the expected use of AI. Figure 1a plots these AI-related texts, demonstrating the richness of information therein.

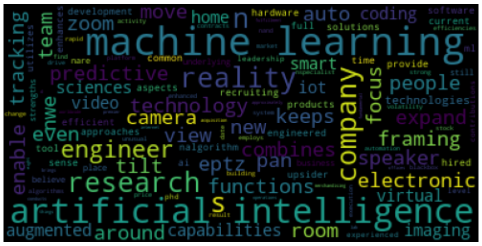
Which firms are adopting AI? My first finding is a rapid growth in AI adoption in US firms, with significant cross-section differences. The fraction of firms that mention AI in filings increased from less than 10% in 2016 to more than 30% in 2022, reflecting a growing interest in and importance of AI in the economy. In the cross-section, some industries experienced much higher growth in AI mentions (e.g., Information, Educational Services, Administrative, and Professional Services) than others (e.g., Mining). Several sectors are highly exposed to AI, with over half of the firms mentioning AI in their filings. On the other hand, some industries are relatively less influenced by AI (e.g., Utilities).

Are AI-adopting firms different from non-adopters? I find AI adoption firms are more efficient in both using labor to generate sales also in faster inventory turnovers. At the same time, these firms employ lower leverage and pay less dividends to shareholders. I also find that AI firms have higher market-to-book ratios, consistent with the findings of positive investor responses to AI-exposed portfolios by Eisfeldt et al. (2023).

How do firms think about AI? I zoom into the AI discussions using GPT (OpenAI, 2022), a large language model. I find that firms hold a predominantly positive perspective on the impact of AI, recognizing its potential benefits (e.g., improved efficiency). Firms also actively consider the implications of AI on jobs and investments, indicating a potentially large impact on the labor market in the near future. Importantly, in terms of timeline, most firms are just beginning to adopt AI, therefore most of the AI impact on either financial or labor markets is still yet to be realized and, therefore hard to measure from a bottom-up approach. Finally, I find most firms exhibit an active approach to embracing AI instead of being passively exposed to AI technology.

Will AI displace human workers? Will AI create new tasks? While these questions have distinctly different first-order economic implications (Acemoglu and Restrepo, 2018), answering them has been a standing challenge for existing AI exposure measures that rely on the capability of AI. My new measure fills in this gap and provides the first answers to these questions. Firm communications (e.g., filings and earnings calls), together with the growing intellectual capabilities of LLM (Bubeck et al., 2023), provide a unique opportunity to explore whether managers think these implementations are labor-augmenting or labor-displacing. Based on the GPT labels, most firm filings imply the use of AI is mostly labor-augmenting and can increase worker productivity, while also having the potential to displace workers. AI is not likely to create new tasks for human workers based on information in most of the firm's filings.

To the best of my knowledge, this is the first measure of AI economic impact based on firms communications. This new measure provides several unique benefits: The filings-based AI impact measure is derived within the context of firms' objectives as a whole by managers and reveals the motivations that drive firms' AI strategies. This component of AI impact would not have been possible via labor task exposure.



(a) Word cloud of AI discussions in firm filings.

(b) Word cloud of GPT labels.

Figure 1: Word clouds of keywords in filings and impact labels.

This paper is also one of the first analysis of firm filings with GPT-3.5, a large-language model (LLM), which allows us to gain a deeper understanding of the business sector response to AI. This novel methodology provides a new entry point to differentiate between the labor-augmenting and -automation effects of GPT, a standing challenge for labor-based measures. LLM allows us to go beyond simply quantifying the extent of AI adoption and allow us to delve into the underlying factors that shape firms' strategic actions related to AI. In relation to labor-based LLM analysis, I obtained a deeper understanding of firms' AI strategies, thereby providing a more comprehensive picture of the business sector's response to AI. Specifically, I uncovered important qualitative aspects, such as the motivation and the expected implications from a managerial perspective, which would not have been possible with either traditional textual analysis or LLM analysis on labor tasks.

In terms of policy implications, this paper bridges the gap between the growing literature on the economic aspects of AI and firms' actual practices and policies. This approach holds the potential to inform stakeholders about both the firm's actions regarding AI and the implications of AI for the business landscape. For policymakers, the new measure provides a unique perspective from firm managers in light of the recent debates about AI regulation.

This paper belongs to the emerging literature on measuring AI exposures (Webb, 2020; Felten et al., 2018; Brynjolfsson et al., 2018; Eloundou et al., 2023; Babina et al., 2024) and the social and economic aspects of machine learning and AI (e.g. Acemoglu and Restrepo (2018); Brynjolfsson and Mitchell (2017); Eisfeldt et al. (2023)). The labor impact of AI has been a focal point of research, in particular, with an emphasis on task-based exposure. Research in this domain has relied on frameworks of task model of automation (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; Autor et al., 2006; Van Reenen, 2011; Acemoglu and Restrepo, 2022). More recently, Eloundou et al. (2023) shows the labor impact of GPTs is likely pervasive. Eisfeldt et al. (2023) study the impact of generative AI on firm value. Using worker resume data, Babina et al. (2024) find AI-investing firms grow faster and have increased innovation. This paper differs from and complements previous literature mainly in our AI exposure measures and methodology, I use a top-down approach starting with firm communication for AI exposure measures and rely heavily on information in these firm communications instead of a bottom-up approach of labor task-based measures.

Our filing-based measure is related to and complements task-based measures because managers may have considered labor task exposures in making managerial decisions. Conversely, the business response may induce changes in labor demand and have implications for the labor market.

This paper leverages the wealth of information contained within firms' filings therefore related to a vast literature using textual analysis on firm filings. For a review of this strand of literature, see Loughran and McDonald (2016). These reports serve as comprehensive documents that provide insights into firms' strategies, investments, and performance. By specifically examining the mentions of AI within these reports, I can discern the extent to which AI is being integrated into firms' operations, products, and services. This approach allows us to assess the economic impact of AI from a corporate perspective, offering a more granular and context-specific understanding of its effects.

2 Methods

My research methodology encompasses several sequential steps to provide a comprehensive assessment of the economic impact of AI. First, I obtain a version of all annual and quarterly filings from 2016 to 2022 made by firms to the U.S. Securities and Exchange Commission's EDGAR (Electronic Data Gathering, Analysis, and Retrieval). Listed firms are required to file filings to the US SEC annually. These reports contain useful information about the operation of firms and managerial assessments. SEC describes these reports as "a comprehensive overview of the company's business and financial condition".[1]

I search the filings to identify the mentions of machine learning and artificial intelligence within their content. Specifically, I search each report to see if it contains either "machine learning" or "artificial intelligence". I say a firm has AI mention to mean mentioning of either "machine learning" or "artificial intelligence" hereafter. Once I identify these references to AI, I extract the whole sentence containing these keywords and compile a dataset comprising the discussions related to AI from the filing.

Using this newly assembled data, I produce statistics about the fraction of unique firms with AI mentions. Specifically, I say a firm mentions AI in a given year if there is at least one filing within the year that contains at least one AI mention. I perform the analysis both at the aggregate US firms level over time as well as on the cross-section of diverse industries. I use the 2-digit NAICS industry code as an identifier of industries for firms. I identify firms by their CIK identifiers. The fraction of firms that mention AI in a given year is calculated as the number of unique firms that mention AI divided by the total number of unique firms with a filing in a given year.

To gain deeper insights and annotate these discussions effectively, I leverage the advanced language processing capabilities of the GPT-3. I use "gpt-3.5-turbo" to assist us in analyzing and annotating the extracted text, allowing us to evaluate the impact of AI as conveyed in the discussions. This method of using GPT to label text is also used in,

[1] see https://www.investor.gov/introduction-investing/investing-basics/glossary/form-10-k

among others, Eloundou et al. (2023); Eisfeldt et al. (2023).

In our annotation process, I ask GPT to provide assessments of the direction and magnitude of the AI impact for each discussion, as well as other aspects of potential impact. Specifically, I ask GPT to classify each text as having a positive or negative impact. Additionally, I ask GPT to label the significance of the impact as high, moderate, or low and evaluate the primary topic of impact. Finally, I ask GPT to differentiate between active and passive exposure to AI.

I prompt the GPT as follows:

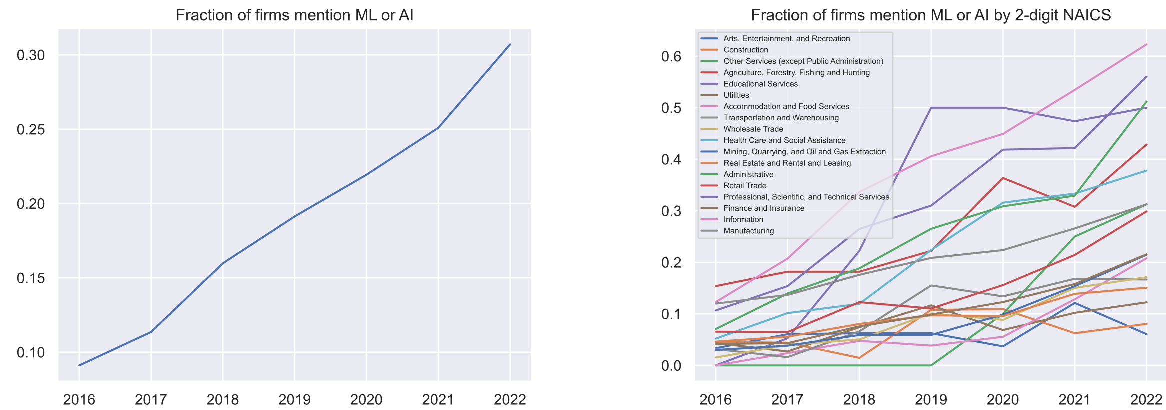
""" System: You will be provided AI-related text from a firm's filing. If the text is not about AI, answer "NA" for all items below. Provide an answer in a list of 5. Your task is to analyze the overall impact of AI and label the following 5 aspects. Think step by step, and choose only one from each aspect.

[ASPECTS: 1. direction of impact: positive, negative, other. 2. significance of impact: low, moderate, high, other. 3. primary topic of impact: labor, investment, revenue, competition, M&A, other. 4. timeline of impact: happened, current, planning, other. 5. aggressiveness of impact: active, passive, other.]

User: ["We continue to see opportunity to offer our fraud detection solutions with advanced machine learning capabilities to help customers"]

Assistant: [positive,moderate,revenue,current,passive] """

In the data cleaning step, I excluded some filings in the final sample. Specifically, I exclude discussions that are over 100 words in context, to avoid distractions and reduce complexity. I also exclude cases where GPT incorrectly labels texts, these include: selecting more than one topic of impact in some cases and failing to generate a high-level analysis of impact.



(a) All US

(b) Industries-specific

Figure 2: The fraction of firms mention Machine Learning (ML) or Artificial Intelligence (AI) in filings.

3 Results

3.1 The growing fraction of filings mention AI

I first note that there is a growing fraction of firms that mention AI in filings, with different rates of growth across industries.

Figure 7d displays the aggregate trend of AI discussions in filings. The data shows a steady increase in AI mentions from 2016 to 2022.[2] The mentions of AI increased from 10% in 2016 to more than 30% in 2022. This indicates a growing interest in and recognition of AI in the economy. The rise in AI mentions accelerated notably from 2017 onwards, with a sharp increase observed in 2017-2018. The data suggests that AI has gained substantial attention and prominence in recent years, reflecting its growing influence and impact on various fields.

I next look into the cross-section of industries. Figure 2b displays the cross-section variation of AI mentions in filings for top industries based on the fraction of firms that mention AI in 2021. Table 1 reports the fractions of firms mentioning AI in 2016 and 2022, along with the average and standard deviation of the yearly growth rate in this period.

[2]Few firms are mentioning AI before 2016.

Table 1: The growth of AI mentions. Columns 2016 and 2022 contain fractions of firms that mention AI. Avg. Growth is the mean of yearly percentage changes; Std. Growth is the standard deviation of yearly percentage changes. Fractions above 50% are in bold.

Industry	**2016**	**2022**	**Avg. Growth**	**Std. Growth**
Arts, Entertainment, and Recreation	0.03	0.06	0.369	1.043
Construction	0.05	0.08	0.917	2.670
Other Services (except Public Administration)	0.00	0.31	∞	NaN
Agriculture, Forestry, Fishing and Hunting	0.15	0.43	0.213	0.280
Educational Services	0.00	**0.50**	∞	NaN
Utilities	0.04	0.12	0.369	0.792
Accommodation and Food Services	0.00	0.21	∞	NaN
Transportation and Warehousing	0.03	0.17	0.677	1.341
Wholesale Trade	0.02	0.17	0.594	0.628
Health Care and Social Assistance	0.05	0.38	0.434	0.391
Mining, Quarrying, and Oil and Gas Extraction	0.03	0.21	0.407	0.242
Real Estate and Rental and Leasing	0.05	0.15	0.230	0.188
Administrative	0.07	**0.51**	0.420	0.323
Retail Trade	0.07	0.30	0.328	0.356
Professional, Scientific, and Technical Services	0.11	**0.56**	0.337	0.243
Finance and Insurance	0.04	0.22	0.331	0.236
Information	0.12	**0.62**	0.330	0.255
Manufacturing	0.12	0.31	0.175	0.069

When examining the cross-industry differences in the mention of AI, distinct patterns emerge.

In 2022, several industries with AI mention fractions surpassing 0.5. The industries are Information, Educational Services, Administrative, and Professional Services. Educational Services experienced remarkable growth, with the AI mention fraction rising from 0.0 in 2016 to 0.5 in 2022, indicating a significant emphasis on AI integration within the sector. Professional, Scientific, and Technical Services also demonstrated a remarkable increase, with the AI mention fraction reaching 0.56 in 2022, highlighting the industry's strong adoption and integration of AI technologies. Among these sectors exhibiting high-growth rates in AI adoption, the Information sector emerges as a clear leader. Notably, the fraction of AI mentions in this sector experienced a steady upward climb, soaring from 0.12 in 2016 to 0.62 in 2022. This high growth trajectory underscores the pivotal role of AI within these industries.

Sectors with smaller fractions of AI mentions include the Arts, Entertainment, and

Recreation sector, and the Construction sector. The AI mentions fraction for the Arts rose from 0.03 in 2016 to 0.06 in 2022. The AI mentions fraction increased from 0.05 in 2016 to 0.08 in 2022 for construction. While these sectors displayed modest fluctuations in the fraction of AI mentions, the overall adoption rates remained relatively low compared to other industries. The disparity with high growth sectors may be attributed to the intrinsic nature of these sectors, which heavily rely on human creativity, physical construction, and personalized customer service. However, even within these sectors, I observed subtle increases in AI adoption, suggesting a nascent interest in leveraging AI technologies to augment efficiency and augment traditional practices.

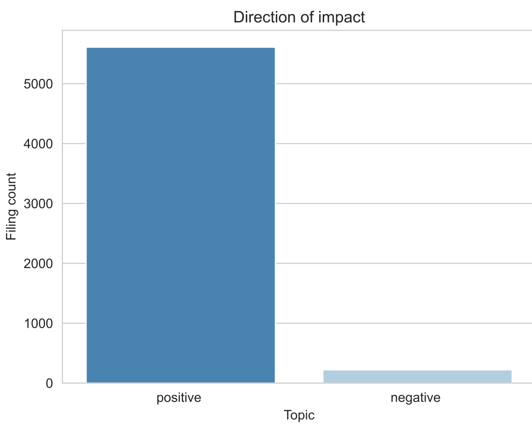
Another intriguing set of sectors worth noting are Other Services (except Public Administration); Education; and Accommodation industries. These industries stood out as having no firms mentioning AI in their filings in 2016. However, in 2022, a significant fraction of firms within these sectors began incorporating AI into their operations, marking a noteworthy transformation.

3.2 GPT labeled AI Discussions in filings

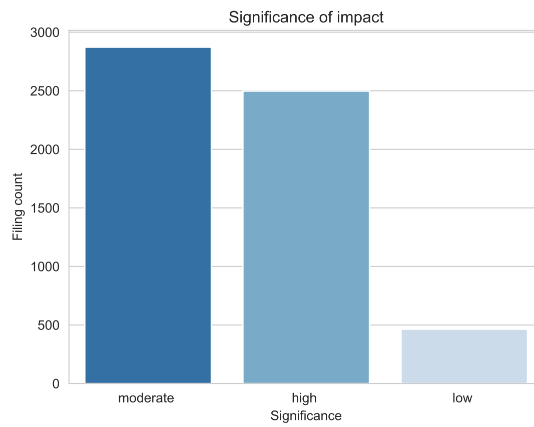
In order to delve deeper into the response of various business sectors to the rise of AI, I employed an annotation process using GPT-3 to analyze AI-related discussions within company filings. By leveraging the language capabilities of GPT-3, I uncover multiple facets related to the implied impact of AI: the direction, significance, primary topic, timeframe, and aggressiveness of the anticipated impact.

Figure 4 illustrates the findings of our analysis. It becomes apparent that, on a general level, firms tend to agree on the positive direction of AI's impact. However, there is less consensus regarding the significance, primary topic, and timeline of the anticipated impact. This suggests that while businesses acknowledge the positive overall direction AI will have on their operations, they hold differing views on the specific areas within their industry that will be most affected, the degree of impact those areas will experience, and the timeline for when these effects will become more pronounced.

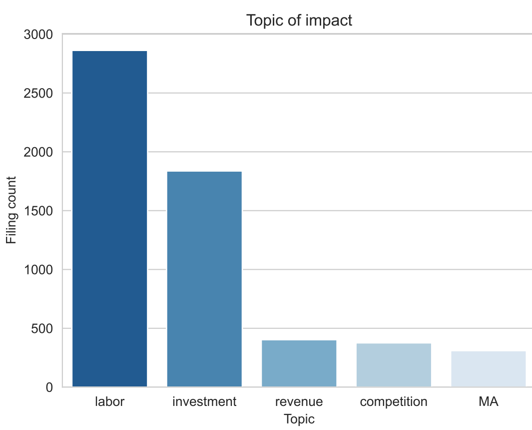
In Table 2, I present the frequency distribution of each label derived from our analysis.



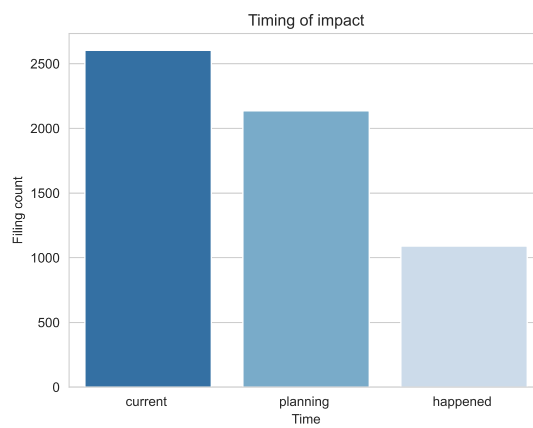
(a) Direction



(b) Significance



(c) Topic



(d) Time

Figure 3: Number of filings for labels.

Table 2: GPT label frequencies calculated within different aspects of impact. The highest frequencies are bolded.

Aspect	**Label**	**Frequency**
Direction	positive	**0.9618**
	negative	0.0382
Significance	moderate	**0.4924**
	high	0.4281
	low	0.0795
Topic	labor	**0.4945**
	investment	0.3174
	revenue	0.0696
	competition	0.0650
	M&A	0.0536
Time	current	**0.4465**
	planning	0.3664
	happened	0.1871
Aggressiveness	active	**0.9324**
	passive	0.0676

Table 3: GPT label for differentiating labor impacts of AI.

Aspect	Label	Frequency
create new tasks	no	**0.7476**
	uncertain	0.0257
	yes	0.2267
displace workers	no	0.1364
	uncertain	0.3799
	yes	**0.4837**
increase worker productivity	no	0.0037
	uncertain	0.0331
	yes	**0.9633**
mostly labor-displacing	no	**0.6091**
	uncertain	0.3143
	yes	0.0766
mostly labor-augmenting	no	0.2434
	uncertain	0.0761
	yes	**0.6805**
impacted Occupations (SOC)	Architecture and Engineering Occupations	0.1013
	Business and Financial Operations Occupations	0.1708
	Computer and Mathematical Occupations	**0.3828**
	Healthcare Practitioners and Technical Occupations	0.1758
	Office and Administrative Support Occupations	0.1693

At a high level, the majority of firms express a positive perspective on AI impact, considering it to be of moderate to high significance. Topics such as labor and investment are frequently mentioned, emphasizing the importance of workforce implications and strategic investments. Firms primarily discuss the current state of AI impact, while considering both future implications and past experiences. Finally, firms exhibit an active approach, indicating a proactive stance in leveraging AI technologies.

Regarding the direction of AI impact, our analysis revealed that the majority of firms view AI in a positive perspective. This is evident from the high frequency of the "positive" label, which accounted for 96.18% of the reported AI impact labels. Conversely, the occurrence of the "negative" label was relatively infrequent, representing only 3.82% of the reported AI impact labels.

In terms of the significance of AI impact, the analysis reveals interesting patterns. The "moderate" label appeared most frequently (49.24%), indicating that firms often consider the impact of AI to be of moderate significance. This is followed by the "high" label (42.81%), suggesting that a substantial number of firms perceive AI to have a significant impact. However, the "low" label (7.95%) also indicates that a minority of firms perceive AI impact to be of low significance.

Examining the frequency of AI impact labels based on topic, it is evident that the most prevalent topic is "labor" (49.45%). This suggests that firms frequently discuss the impact of AI on their workforce, including aspects such as automation and workforce restructuring. Indeed, Eloundou et al. (2023) find 80% of the U.S. workforce would have more than 10% exposure to LLM alone. The topic of "investment" also garnered considerable frequency (31.74%), indicating that firms are at least considering the importance of investing in AI. Additionally, topics such as "revenue" (6.96%), "competition" (6.50%), and "M&A" (5.36%) were mentioned, albeit with lower frequencies.

Turning to the aspect of timing, the "current" label appeared most frequently (44.65%), indicating that firms primarily discuss the current state of AI impact. The label "planning" (36.64%) suggests that firms also consider the future implications of AI on their operations. The label "happened" (18.71%) reveals that some firms retrospectively reflect on past AI impacts.

The analysis of AI impact labels related to aggressiveness reveals that the majority of firms exhibit an "active" approach (93.24%). This suggests that firms actively pursue AI initiatives and perceive AI impact as a proactive strategy. Conversely, the "passive" label (6.76%) indicates a smaller portion of firms that adopt a more reactive or cautious approach to AI impact.

4 The implied economic impact of AI

The findings of our study thus far reveal a noticeable increase in the interest and attention given to AI based on the frequency of AI impact discussions within firms' filings. This trend signifies that businesses are becoming increasingly aware of the importance and relevance of AI in their operations, as well as the potential it offers for fostering innovation and driving growth. The presence of AI-related discussions in these filings reflects a proactive approach by firms to communicate their engagement with AI technologies and express their assessment of its impact on their business operations. By including AI-related information in their filings, firms are signaling their recognition of AI's significance and its potential implications for their industry and competitive landscape.

The analysis reveals that certain sectors, such as information, exhibit a higher interest in AI impact compared to others. The higher frequency of AI impact discussions suggests that these industries perceive AI as particularly relevant to their operations. The reasons behind this sector-specific interest may include factors such as the nature of the industry, the potential for AI-driven disruptions, and the recognition of AI as a critical enabler of competitive advantage. Understanding these variations in sector-specific interest can provide valuable insights into the targeted adoption of AI technologies and strategies.

The limited presence of the "negative" label suggests that concerns regarding the negative implications of AI are less prevalent among the firms analyzed in our study, which itself could be a risk factor for the firm. Furthermore, there are potential negative societal risks need to be accounted for. Therefore our analysis also highlights a crucial need for organizations to carefully address the potential risks and challenges associated with AI adoption, for example, data privacy and security, job displacement, algorithmic biases, etc.

The presence of discussions surrounding labor indicates that firms are actively considering the implications of AI on jobs and the workforce. This suggests a recognition of the need for job transformation and the development of new skills to align with AI-driven workflows. Firms are likely to acknowledge the potential changes AI can bring to jobs and are actively strategizing to ensure their workforce remains relevant and capable in an AI-driven environment. Furthermore, the emphasis on investment underscores the understanding of AI as a strategic imperative. Firms recognize that AI has the potential to drive significant value and competitive advantage. To fully exploit this potential, dedicated resources are required. The labor and investment aspects discussed in the filings suggest that firms are not only aware of the transformative potential of AI but also actively engaging in efforts to adapt and leverage its benefits. This proactive mindset indicates a forward-thinking approach, where organizations are taking steps to ensure their workforce is equipped with the necessary skills and are making strategic investments to capitalize on the advantages that AI can offer.

I also find that most of the impact of AI on the business sector is likely yet to come. Firms primarily focus on the current state of AI impact while considering both future implications and past experiences. This suggests that firms are mindful of the evolving nature of AI and its potential long-term effects. By considering past impact, firms can draw insights from previous AI initiatives and use them to inform their current and future strategies.

Finally, I find that firms exhibit an active approach on AI exposure, demonstrating a proactive stance in leveraging AI technologies. This implies that firms are actively seeking opportunities to adopt and integrate AI into their operations, recognizing its potential as a strategic enabler. The positive perspective expressed by firms and their active engagement with AI highlights a proactive stance in embracing AI-driven transformations.

4.1 Labor-augmenting and labor-displacing effects

A standing challenge for existing methods is how to differentiate between Labor-augmenting and labor-displacing effects. In traditional task-based approaches, this is difficult to achieve, because a high AI capability does not necessarily translate to displacing human workers.

In using GPT to analyze the labor impact of AI, I'm guided by Acemoglu and Restrepo (2018). The analysis differentiates the labor impacts of AI and focuses on four key aspects: "create new tasks," "displace workers," "increase worker productivity," and whether AI is "mostly labor-displacing" or "mostly labor-augmenting."

The analysis indicates AI will create some new tasks for human workers. with 22.6% of filings involving the creation of new tasks.

Regarding the displacement of workers, my findings indicate a notable potential for AI to displace workers: 13.64% of filings were labeled as "no," 37.99% as "uncertain," and 48.37% as "yes.".

In a task-based framework, I find knowledge work activities are more exposed than physical work activities. And the use of AI on non-creative tasks such as "Documenting/Recording Information" are more likely to be automated and displace workers.

5 Limitation

In this section, I discuss a few technical limitations, focusing on the reliance on filings and the potential absence of explicit discussions regarding the impact of AI in these reports.

5.1 Reliance on public firms

The foundation of my analysis relies on the availability of filings, which provide information on the financial performance, operations, and strategic direction of companies. A challenge arises due to the differential reporting requirements between public and private firms. While public firms are obligated by law to submit filings to regulatory authorities, private firms do not have the same requirement. Consequently, our access to comprehensive and standardized data may be constrained when it comes to private companies. While a typical public firm generally has larger sizes and more employees than a private firm in the same sector. However, it is essential to acknowledge that this potentially limits the generalizability of our findings to the private business landscape.

5.2 Reliance on GPT's capabilities

An integral part of our research methodology is the LLM annotation process, which relies on the language understanding capabilities of GPT-3. GPT plays a crucial role in accurately understanding and extracting relevant information from the text scripts of filings.

GPT has been extensively trained on a diverse range of texts, and have demonstrated remarkable proficiency in processing and comprehending natural language (Bubeck et al., 2023). However, it may encounter challenges in accurately interpreting certain complex or domain-specific language used in filings. These challenges may arise due to ambiguous phrasing, technical jargon, or the idiosyncrasies of financial reporting. In this work, I mitigate this limitation by excluded incorrectly labeled discussions. In the next step, I also plan to use alternative language models to validate the results from GPT.

5.3 Reliance on AI discussions by firms

Another limitation arises from the reliance on AI discussions potential absence of explicit discussions regarding the impact of AI in the filings of some companies. While AI technologies are increasingly shaping the business landscape, not all firms may choose to address its specific impact in their filings. This omission can pose challenges when attempting to capture and analyze the comprehensive landscape of AI adoption and its implications. Nevertheless, filings encompass a wide range of reporting requirements, including the disclosure of risk factors. For example, SEC requires firms to "Provide any discussion of risk factors in plain English in accordance with Rule 421(d) of the Securities Act of 1933 ...".

5.4 Mimicry of AI initiatives

Firms may mimic one another's strategies and practices, leading to a lack of distinctiveness and innovation. When innovative companies began the integration of AI into business, non-innovative firms may find it difficult to distinguish themselves in the competitive market, therefore simply imitating other AI strategies. This mimicry can create a more skewed distribution, making it challenging for researchers to discern the real economic impact of AI.

6 Conclusion

In this paper, I introduce a novel measure of the economic impact of AI. I capture real-world, firm-level data that reflects the actual integration and utilization of AI technologies. This approach opens up new avenues for understanding the economic impact of AI and informs policymakers, practitioners, and researchers about the opportunities and challenges associated with this transformative technology.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in us wage inequality. *Econometrica*, 90(5):1973–2016.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The polarization of the us labor market. *American economic review*, 96(2):189–194.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.

Brynjolfsson, E. and Mitchell, T. (2017). What can machine learning do? workforce implications. *Science*, 358(6370):1530–1534.

Brynjolfsson, E., Mitchell, T., and Rock, D. (2018). What Can Machines Learn and What Does It Mean for Occupations and the Economy? *AEA Papers and Proceedings*, 108:43–47.

Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., Lee, P., Lee, Y. T., Li, Y., Lundberg, S., Nori, H., Palangi, H., Ribeiro, M. T., and Zhang, Y. (2023). Sparks of Artificial General Intelligence: Early experiments with GPT-4. *arXiv*.

Eisfeldt, A. L., Schubert, G., and Zhang, M. B. (2023). Generative AI and Firm Values. *SSRN Electronic Journal*.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. *arXiv*.

Felten, E. W., Raj, M., and Seamans, R. (2018). A method to link advances in artificial intelligence to occupational abilities. *AEA Papers and Proceedings*, 108:54–57.

Loughran, T. and McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, 54(4):1187–1230.

McKinsey (2021). A new look at how corporations impact the economy and households.

OpenAI (2022). Introducing chatgpt.

OpenAI (2023). Gpt-4 technical report. Technical report, OpenAI.

Thoppilan, R., De Freitas, D., Hall, J., Shazeer, N., Kulshreshtha, A., Cheng, H.-T., Jin, A., Bos, T., Baker, L., Du, Y., et al. (2022). Lamda: Language models for dialog applications. *arXiv preprint arXiv:2201.08239*.

Van Reenen, J. (2011). Wage inequality, technology and trade: 21st century evidence. *Labour economics*, 18(6):730–741.

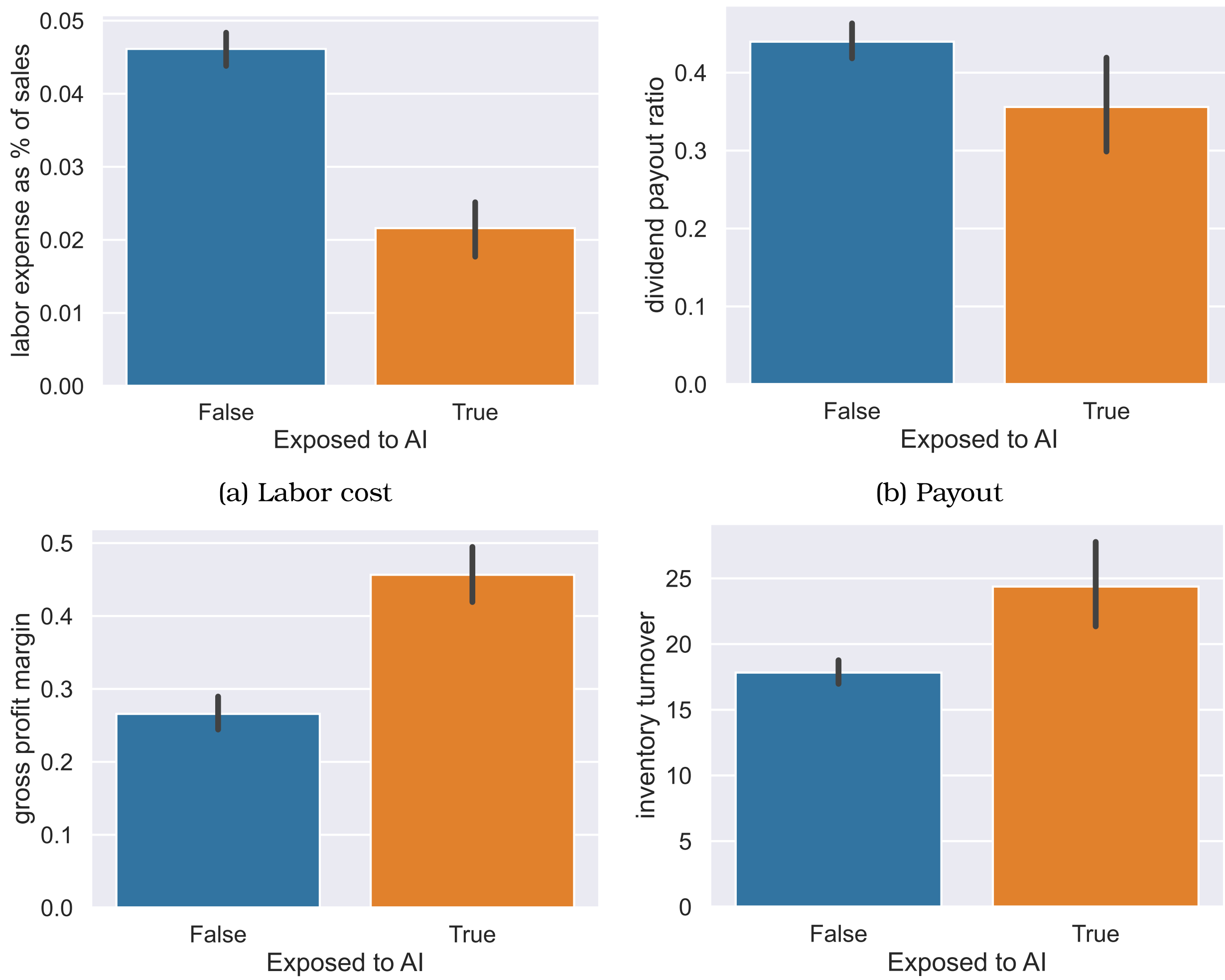
Webb, M. (2020). The impact of artificial intelligence on the labor market. Working paper, Stanford University.

Table 4: Firm performance and AI exposure

This table presents regressions of firm financial ratios on AI exposure, according to $FinRatio_{it} = \beta_0 + \beta_1 \text{AI\_exposed}_i + \beta\Gamma + \epsilon_{it}$ where $FinRatio$ denotes the financial ratio of interest. The explanatory variable is a dummy variable, $AI\_exposed_i$, that equal to one if a firm has communicated about AI in earnings calls and zeroes otherwise. I also include control variables denoted by the vector Γ including the year and industry fixed effects. Industry are defined by their 2-digit NAICS code. The financial ratios used are as follows: In column (1), the dependent variable is labor expense as a fraction of sales. In column (2), the dependent variable is debt to equity ratio. In column (3), the dependent variable is inventory turnover. In column (4), the dependent variable is return on equity. In column (5), the dependent variable is book to market ratio. In column (6), the dependent variable is dividend payout ratio. Finally, in column (7), the dependent variable is gross profit margin.

	staff_sale	de_ratio	inv_turn	roe	bm	dpr	gpm
AI_exposed	-0.02***	-0.33**	2.83**	0.03**	-0.13***	-0.06*	0.06**
	(0.00)	(0.16)	(1.33)	(0.01)	(0.01)	(0.03)	(0.03)
Intercept	-0.01	0.62	-13.40	0.10	1.73***	5.01***	0.07
	(0.07)	(4.56)	(29.70)	(0.34)	(0.30)	(0.83)	(0.84)
Observations	13,036	13,162	9,487	12,350	12,549	9,189	13,036
Adjusted R^2	0.40	0.06	0.24	0.06	0.18	0.03	0.07

Note: *p<0.1; **p<0.05; ***p<0.01



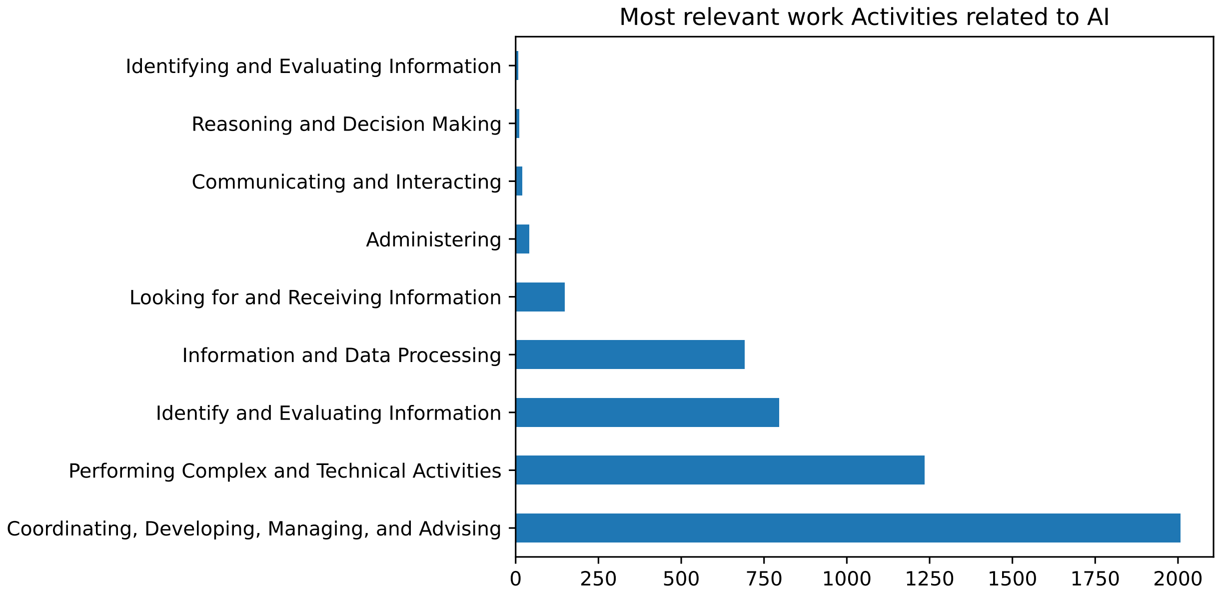
(a) Labor cost

(b) Payout

(c) Profit Margin

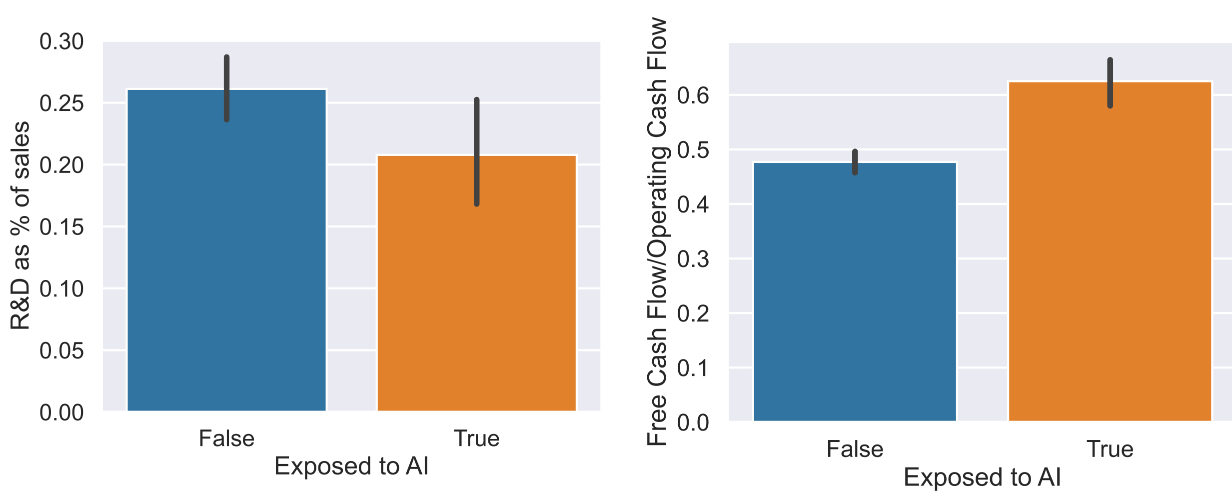
(d) Inventory Turnover

Figure 4: Firm performance and AI



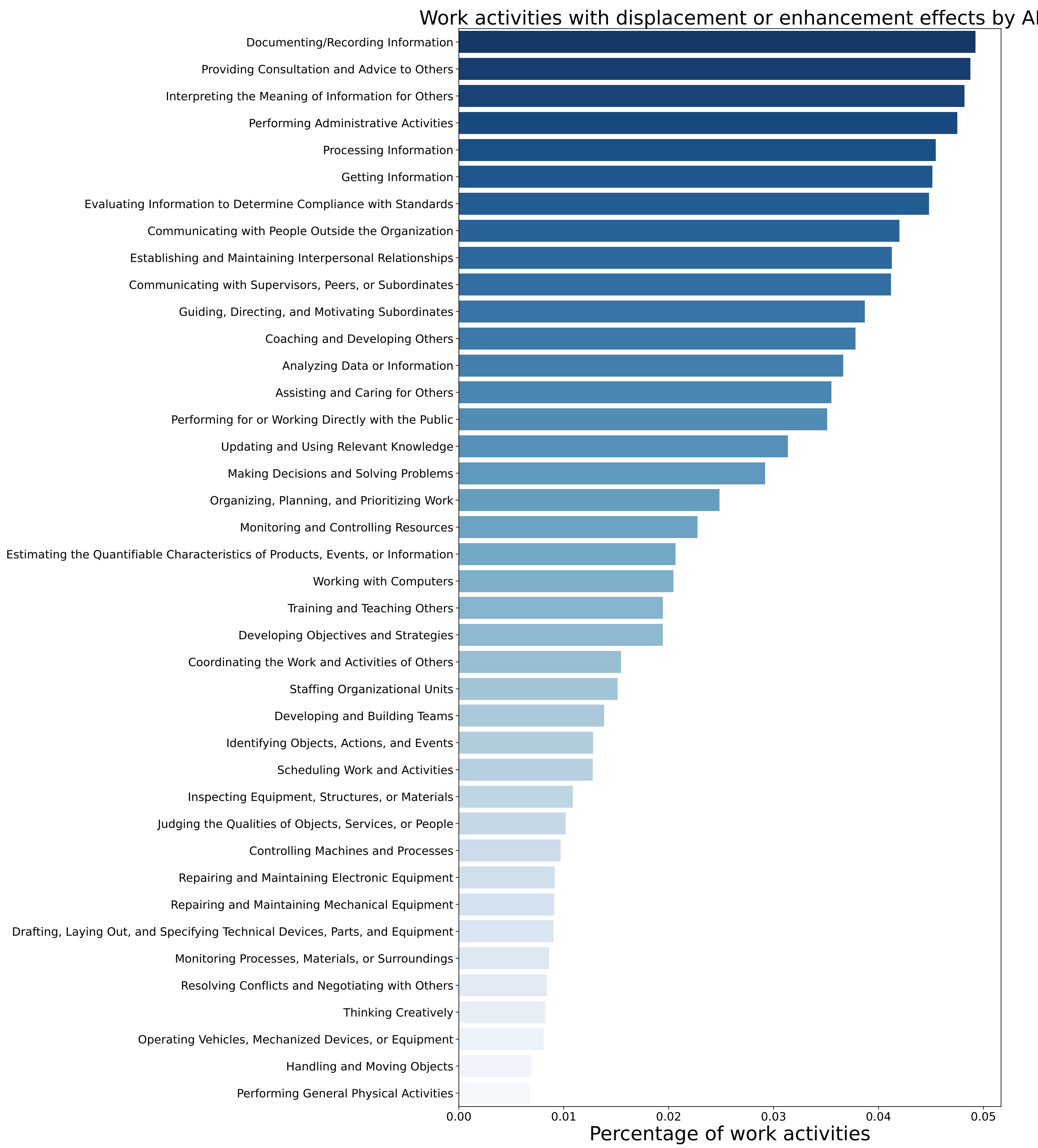
(a) Major Work Content

Figure 5: Most relevant work Activities related to AI

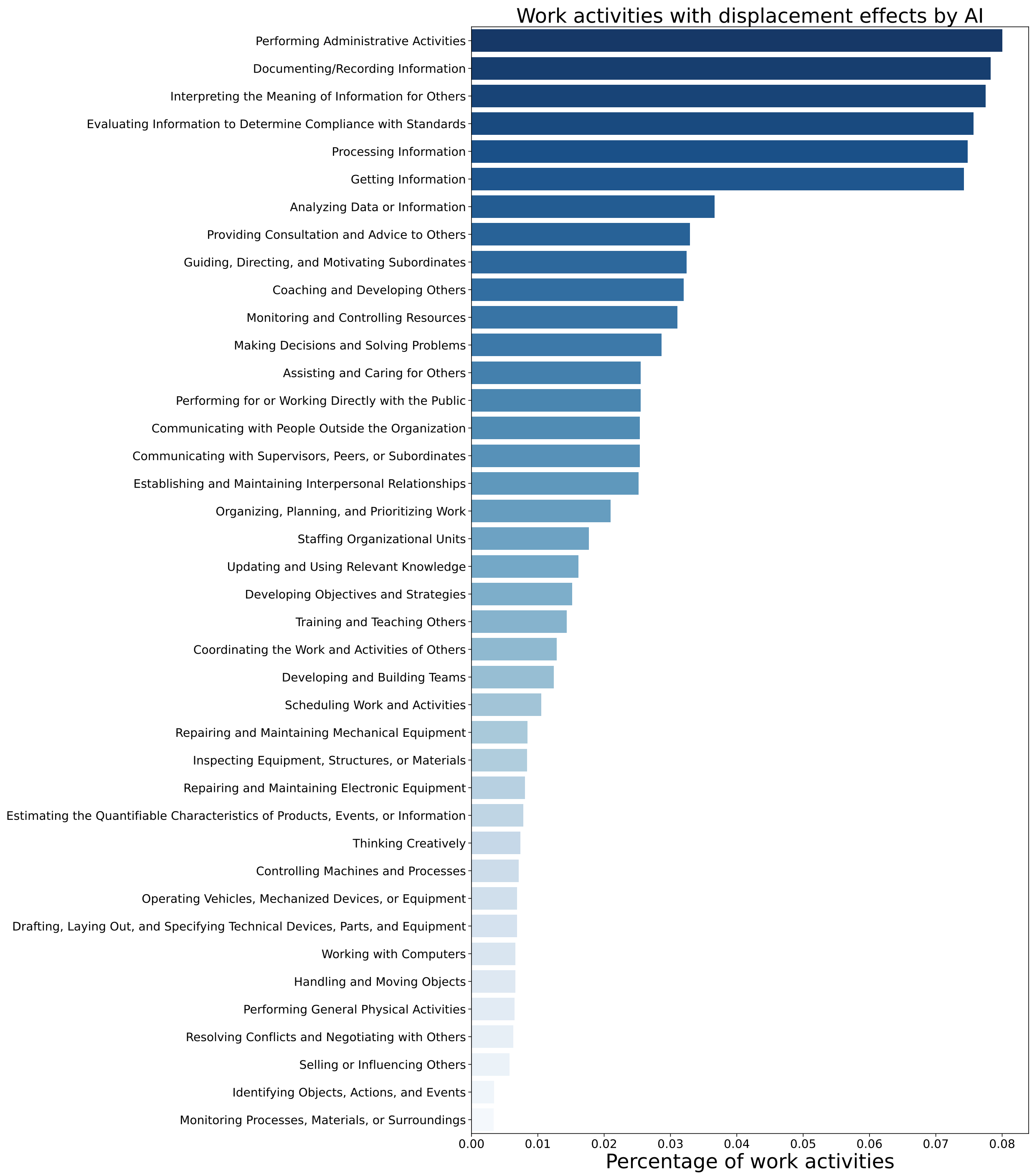


(a) R&D

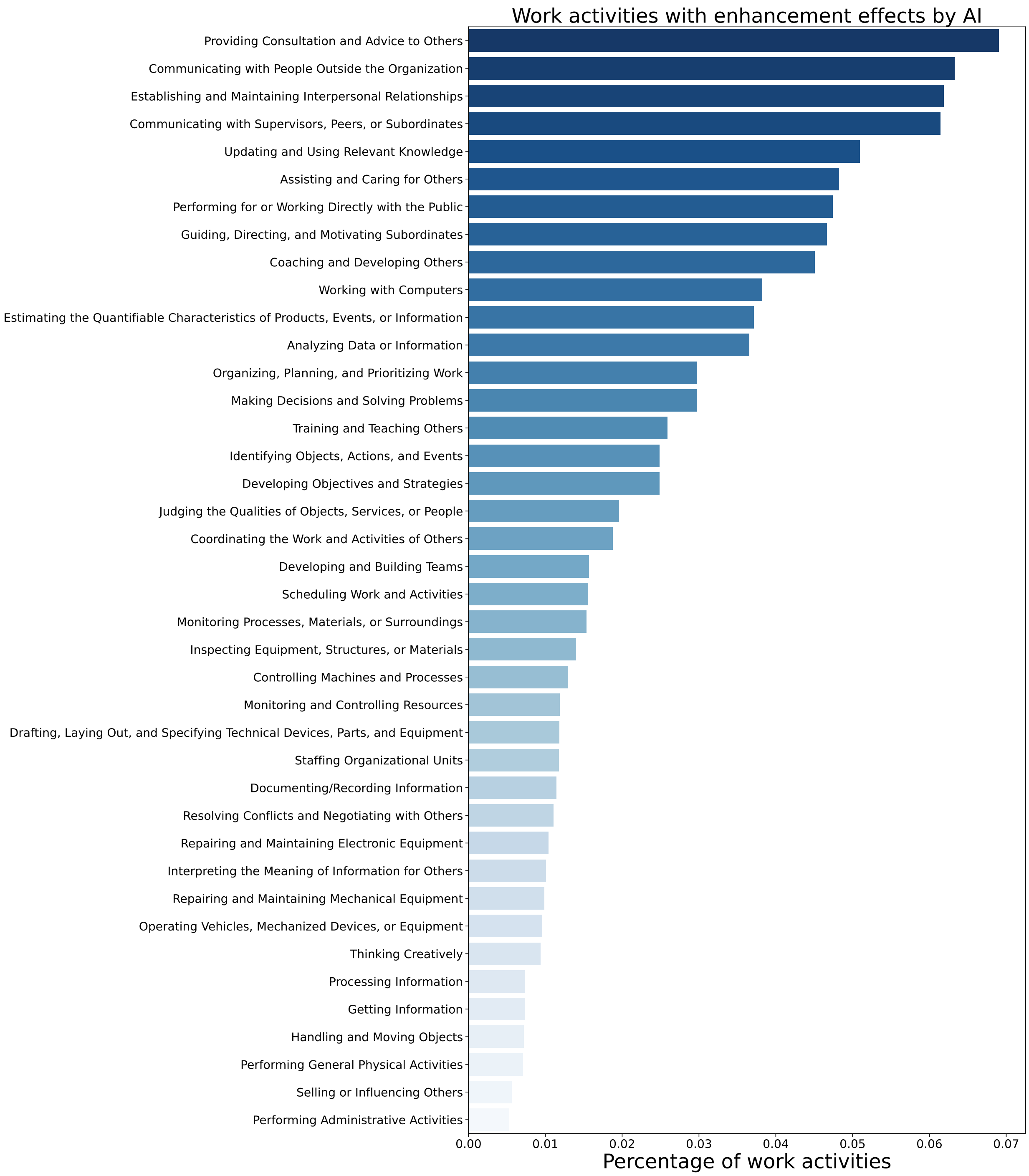
Figure 6: R&D and Free Cash Flow



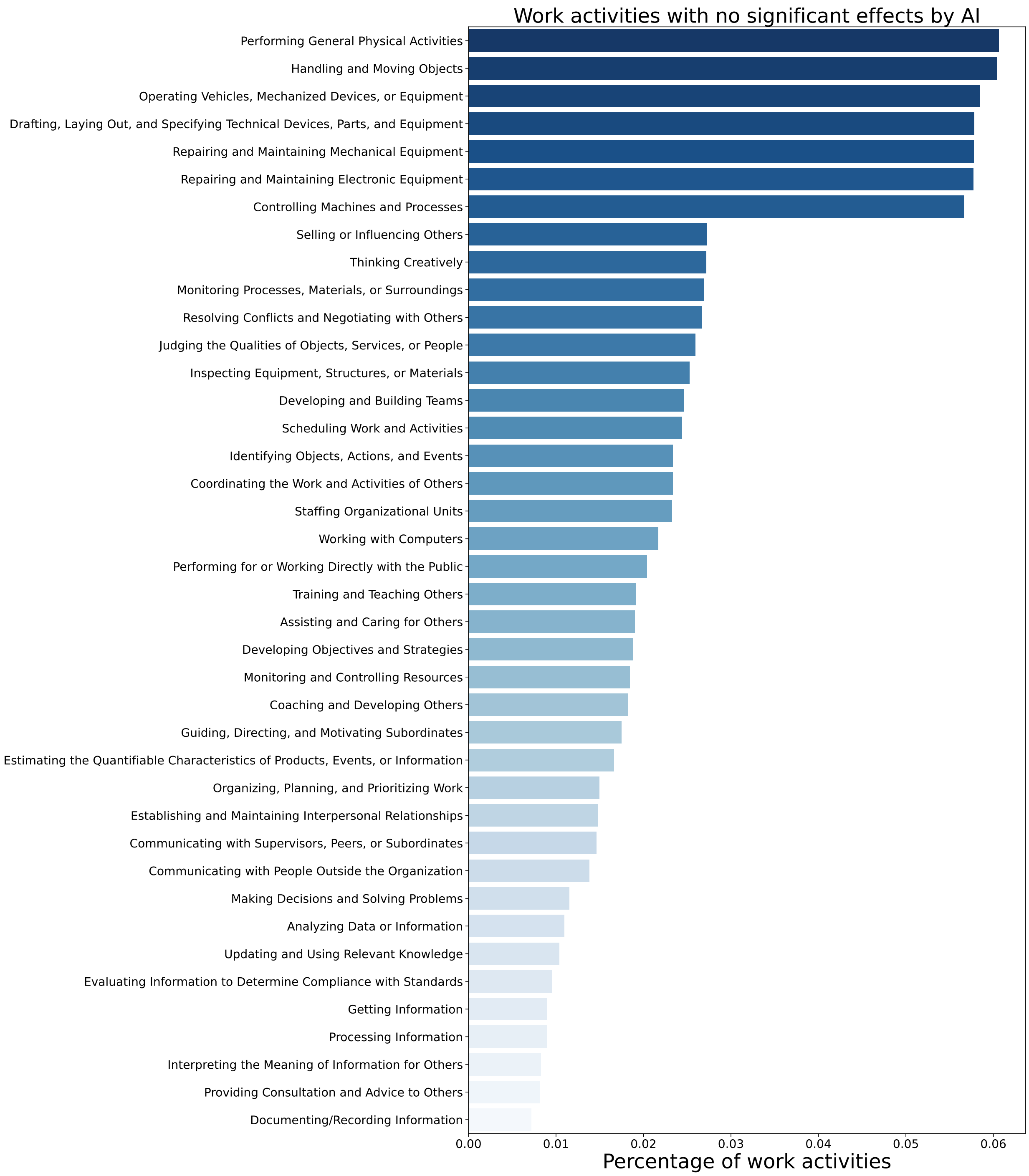
(a) Overall AI exposure on work activities



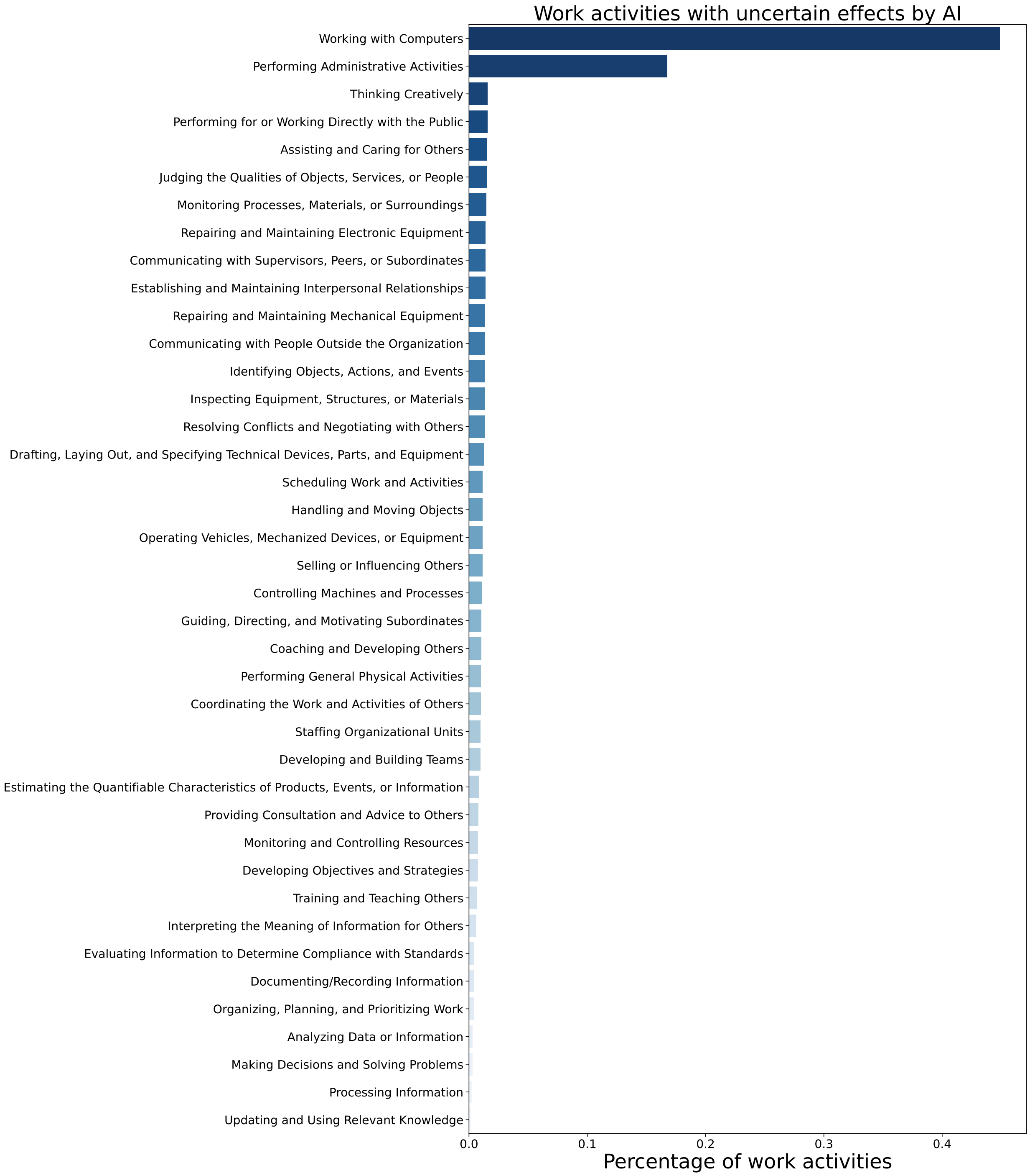
(b) Displacement effect



(c) Enhancement effect



(d) No significant effect



(e) Uncertain effect

Figure 7: AI impact on work activities within firms

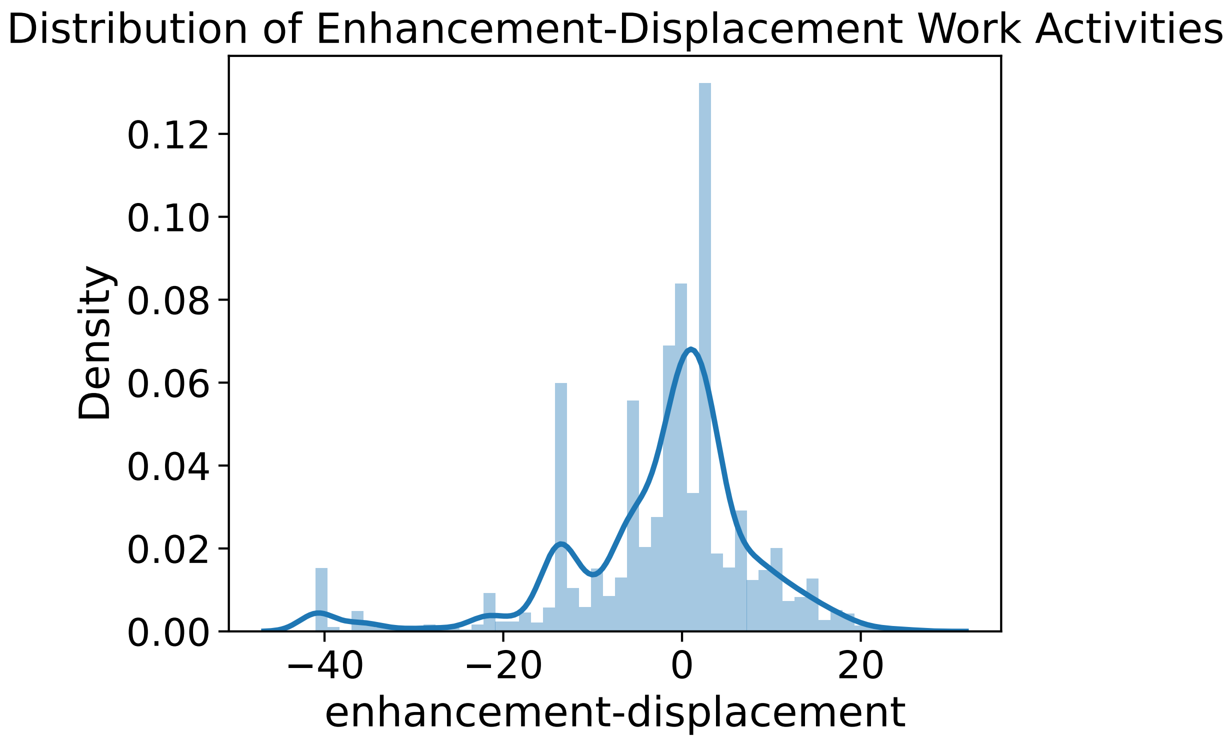


Figure 8: Firm Distribution of Enhancement-Displacement Work Activities