

Generative AI and Firm Values*

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Abstract

What are the effects of recent advances in Generative AI on the value of firms? Our study offers a quantitative answer to this question for U.S. publicly traded companies based on the exposures of their workforce to Generative AI. Our novel firm-level measure of workforce exposure to Generative AI is validated by data from earnings calls, and has intuitive relationships with firm and industry-level characteristics. Using Artificial Minus Human portfolios that are long firms with higher exposures and short firms with lower exposures, we show that higher-exposure firms earned excess returns that are 0.4% higher on a daily basis than returns of firms with lower exposures following the release of ChatGPT. Although this release was generally received by investors as good news for more exposed firms, there is wide variation across and within industries, consistent with the substantive disruptive potential of Generative AI technologies.

Keywords: Artificial Intelligence, Generative AI, Chat GPT, Corporate Valuations, Equity Returns, Technological Change

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Recent advances in Generative Artificial Intelligence are widely seen as a major technology shock with important implications for firm values. Relative to earlier artificial intelligence models, Generative AI models can digest more complex inputs, and can produce human-like output, making Generative AI more versatile and scalable than prior innovations in AI and machine learning. As a result, Generative AI has the potential for widespread corporate adoption, with implications for firm values both across and within a wide array of industries.

One of the biggest questions surrounding advances in Generative AI is what effect these technologies will have on corporate valuations as a result of the impact of Generative AI on firms' labor inputs. We construct a novel dataset containing firm-level workforce exposures to Generative AI. We provide a quantitative measure of the impact of Generative AI based on our firm-level exposure data combined with financial market data. Using this measure we compute the first estimates of the effect of Generative AI on firm values by studying the impact of the release of ChatGPT on firms with varying exposures to the technology shock.¹

We measure the impact of a major event in the advancement and dissemination of Generative AI technology, namely, the public release of ChatGPT, on equity returns at the firm level. This event had a substantial impact on firm returns, consistent with Generative AI advancement representing a major technological shock, one for which we can measure the arrival and impact in real time. While firms may progressively adopt the technology, the unmatched media attention and user base that ChatGPT has garnered within just months indicates that firms and investors are actively assessing the potential fast diffusion of this technology. We show that Twitter mentions and earnings call mentions of Generative AI increased substantially following the release of ChatGPT. Moreover, the massive information gathering and processing ability of ChatGPT itself allows us to assess each firm's exposure to ChatGPT's disruption in real-time.

Our key finding is that the arrival of ChatGPT had a sizable positive effect on the value of firms whose labor forces are more exposed to Generative AI and related Large Language Models (LLMs). Firms with higher exposure to the release of ChatGPT, as measured by the exposure of their labor force to being made more productive by tools like ChatGPT, outperform firms with lower exposures by over 40 basis points in daily excess returns during the two weeks following its release. Notably, these return differences are not only due to across-industries differences in labor force exposures. Returns of firms with high labor force exposures also outperform firms with low exposures by about 40 basis points daily in

¹Recent studies of Generative AI include Eloundou, Manning, Mishkin, and Rock (2023) who study the impact of Generative AI on industries' labor forces, Noy and Zhang (2023) who study the displacement effects of Generative AI on professional writing tasks, and Brynjolfsson, Li, and Raymond (2023) who study the effects of Generative AI on customer support agents, and Felten, Raj, and Seamans (2023) who consider heterogeneity in occupational exposure.

industry-neutral portfolios.

Our methodology builds on the idea that ChatGPT and related technologies will increase firm-level free cash flows through a labor effect that can work through two potential channels. First, firms whose labor force can be substituted for with cheaper Generative AI-based capital will experience higher free cash flows by lowering input costs.² Second, firms whose labor inputs are more complementary to Generative AI will experience higher cash flows due to the technological improvement in an input that is complementary to their workforce.³ We provide evidence consistent with Generative AI being, on balance, more of a substitute for labor inputs using large-scale data on job postings following the release of Chat GPT.

Firms that have a higher share of occupations exposed to Generative AI experience gains in value across a wide array of industries. At the same time, the effect of the release of ChatGPT on firm values varies widely across industries, as well as within industries across firms. Indeed, we find a significantly negative impact from the release of ChatGPT for some industries. Value losses for incumbents are consistent with the idea that for some industries Generative AI will lead to new entrants and displacement of existing firms. While advances in Generative AI can have effects through the product market as well as through the labor market (for example, increasing demand for cloud computing services), our results support the idea that AI advances will have a broad impact on the economy through its effects on labor inputs. The fact that the overall impact of the arrival of ChatGPT on firms with more exposure to Generative AI is significantly positive is consistent with recent studies showing that it is increasingly more difficult for new entrants to displace incumbent firms.⁴

We measure firm-level exposure to Generative AI in two steps. First, we build on Eloundou et al. (2023) and use ChatGPT itself to assess whether each of the 19,265 tasks currently performed by various occupations can be done by the current ChatGPT or by future ChatGPT after investment in additional capabilities. Following Eloundou et al. (2023), we aggregate the task-level exposure measures to the occupations in the O*NET database. Second, and novel to our analysis, we map occupations to publicly-traded firms using data from Revelio Labs. This dataset is constructed from millions of public employee profiles such as LinkedIn. Our firm-level exposure measure thus captures the ability of the tasks currently performed by labor at those firms to be performed (or made more efficient) by Generative AI. To the best of our knowledge, our study is the first to create a firm-level measure of exposure to Generative AI.

We next validate our labor-based measure of firms' exposure to Generative AI by examin-

²See Autor, Levy, and Murnane (2003) and Zhang (2019) for measures of firm exposure to automation and Webb (2019) and Lane and Saint-Martin (2021) for the impact of AI on firms.

³See Krusell, Ohanian, Ríos-Rull, and Violante (2000) and Eisfeldt, Falato, and Xiaolan (2022).

⁴See, for example, Gutiérrez and Philippon (2019) and Akcigit and Ates (2020).

ing firms’ earnings call transcripts in 2023. We document a strong relationship between our measure of exposure to Generative AI and firms’ discussions of Generative AI and related technologies in firms’ earnings calls following the release of ChatGPT. In contrast, firms with higher exposure to Generative AI do not increase discussions common technological topics such as Engineering following the release of ChatGPT. Moreover, these findings remain even after we exclude all firms from the most IT-related sectors,⁵ suggesting that firms’ recent discussions about Generative AI go beyond its impact on related products, and extend to the impact on operations including labor inputs.

We start by showing the types of occupations that will be affected by advances in Generative AI. We find that the most affected occupations are those that involve non-routine cognitive tasks. This is in stark contrast with prior findings for automation. Automation mainly displaces occupations involving routine tasks (Autor et al. (2003)). Indeed, the most affected occupations are those with a high share of non-routine cognitive analytical tasks or routine cognitive tasks, while manual physical tasks are relatively unaffected. Interpersonal tasks lie in between cognitive and manual tasks in terms of their exposure to Generative AI. Occupations with higher wages also have higher exposure to Generative AI.⁶

Exposure to Generative AI through firms’ labor inputs has an intuitive relationship to average firm characteristics across and within industries. At the industry level, more exposed sectors have higher wages, consistent with those sectors employing more workers in higher-paid occupations that also tend to be more exposed to Generative AI. Regarding labor inputs, firms in more exposed industries tend to have higher labor intensity in terms of the number of employees per unit of capital, and lower asset tangibility. More exposed firms also have higher ratios of intangible or organization capital to total capital.⁷ For the characteristics related to firm valuation, more exposed sectors have lower average firm size as measured by total assets and higher Tobin’s Q. Importantly, we also observe similar relationships between firms’ exposure to Generative AI and firm characteristics within industry sectors.

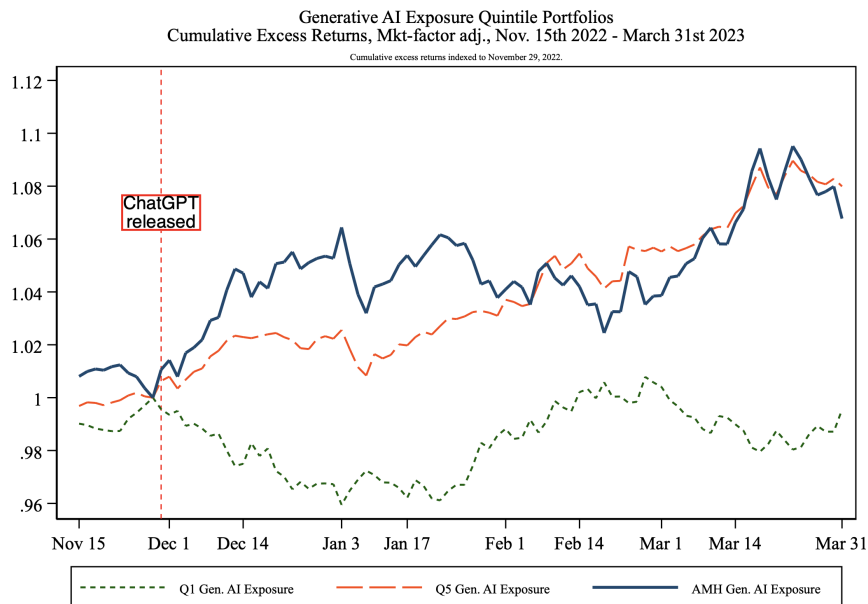
Firms with higher exposure to Generative AI experience higher volatility around the release of ChatGPT. However, it appears that it takes some time for the information in ChatGPT’s release to be impounded into stock prices. The cumulative excess returns for the highest-exposure quintile of firms vs. the lowest-exposure quintile diverge for several weeks following the release of ChatGPT. Figure 1 plots the returns of the highest-exposure

⁵To be precise, we exclude the NAICS 51 “Information” and NAICS 54 “Professional, Scientific, and Technical Services” sectors.

⁶Our result is consistent with recent findings by Kogan, Papanikolaou, Schmidt, and Seegmiller (2019), who find that technological advances impact workers at the higher end of the wage distribution. On the other hand, other studies (Krusell et al. (2000), Eisfeldt, Falato, and Xiaolan (2023)) document substitutability between low-skilled labor and capital but complementarity between high-skilled labor and capital.

⁷See Eisfeldt and Papanikolaou (2014) and Eisfeldt and Papanikolaou (2013).

Figure 1: Generative AI exposure quintile portfolio returns over time: market factor-adjusted. The graph shows the cumulative excess realized returns on portfolios based on value-weighted sorts. All portfolio returns shown are net of the risk-free rate. The data set consists of daily stock returns from Yahoo Finance for Nov. 15, 2022 - March 31, 2023. The figure shows returns adjusted for market factor exposure.



quintile, the lowest-exposure quintile, and a long-short portfolio, which we denote AMH for “Artificial Minus Human”. Cumulative returns to holding the AMH portfolio that is long the highest-exposure quintile, and short the lowest-exposure quintile from the release date through March 31, 2023, are over 7%.

We study the effect of Generative AI on firm values by comparing the returns of firms with higher and lower occupational exposure to Generative AI during and outside the two-week window following the release of ChatGPT on November 30, 2022. The effects are substantial, and monotonic, within industries across Generative AI-exposure quintiles. Adjusting for the market factor, the excess returns to quintile portfolios formed based on firm-level occupational exposure to Generative AI are monotonically increasing, with the highest-exposure quintile of firms within industries earning positive excess daily returns of over 40 basis points while the lowest exposure quintile experiences negative excess returns of around 25 basis points. The fact that these strong effects exist *within* industries for many industries provides evidence that Generative AI can have a broad impact on firm values through the effects on their labor inputs.

Across industries, the effects of Generative AI on firm value also vary widely. Publishing, information and computing-related industries have positive returns following the release of

ChatGPT, while finance and transportation-related industries experience negative returns overall. Dispersion across industry returns is much higher during the two-week period following the release of ChatGPT than over the full sample from November 30, 2022 to March 31, 2023 overall.

Our within-industry results also display striking differences across industry sectors. Within finance, the return of more exposed firms relative to less exposed firms is substantially and significantly positive. Combined with the overall negative industry effect, this is consistent with some firms benefiting greatly from Generative AI advances while overall the impact of the release of ChatGPT was negative for value in the finance industry. Firms with higher exposures to Generative AI within manufacturing as well as the administrative support, waste management, and remediation services industry also significantly outperform firms with lower exposures. On the other hand, firms with higher exposures in the real estate and rental and leasing industry significantly underperform firms with lower exposures. This could mean that existing firms with large exposures to Generative AI may be displaced by new entrants in those industries. Finally, several industries do not display significant return spreads following the release of ChatGPT, including construction of buildings, mining, and heavy and civil engineering construction. The negligible impact in these industries is consistent with manual tasks' lower exposure to Generative AI.

Our study contributes to the literature studying the impact of disruptive technologies on firm valuations.⁸ Papanikolaou (2011) and Kogan and Papanikolaou (2014) study the effects of investment-specific technological changes on asset prices. Zhang (2019) studies firms' exposure to routine-biased automation. In a series of papers, Babina, Fedyk, He, and Hodson (2020), Babina, Fedyk, He, and Hodson (2021), and Babina, Fedyk, He, and Hodson (2022) study the effects of AI on firm growth, compensation, and workforce composition. See also Webb (2019) for the impact of AI on firms. Kelly, Papanikolaou, Seru, and Taddy (2021) study firms' exposure to disruptive technological shocks using patent textual data, and Kogan et al. (2019) assesses worker displacement from technological change over a very long sample. These studies offer important insights into investors' and firms' responses to technological shocks in historical samples.

Our study departs from these works by focusing on measuring firms' exposure to Generative AI and assessing investors' reaction to the technology shock *upon its arrival*. We argue that the release of ChatGPT in November of 2022 is an observable, large technology shock. We also highlight our contribution of measuring investors' reactions to this shock in real-time. Indeed, the information in market prices can potentially inform employees' and

⁸See Greenwood, Hercowitz, and Krusell (1997) for an early contribution on the long-run impacts of investment-specific technological change.

firms’ ultimate responses to technological disruption. Timely assessment of the market’s expectations of Generative AI’s impact on firms can also help policy makers to effectively evaluate regulatory policies in response to the arrival of the new technology.

While other contemporaneous or recent studies such as Eloundou et al. (2023) also address the exposure of occupations to Generative AI advances, our paper is novel in its contributions to the effect on *firms*. Our use of the Revelio Labs data to link occupations to firms yields a unique opportunity to study corporate outcomes.⁹

The paper proceeds as follows: Section I describes our data and measure of firms’ exposure to Generative AI, including descriptive facts about Generative AI exposures across occupations, industries, and firms. Section II presents our results documenting the substantial changes in firm valuations following the introduction of ChatGPT. Section III documents corporate communications to investors regarding Generative AI, and the relationship between those communications and our measure of Generative AI exposures. Section IV provides evidence that generative AI is, overall, a substitute for labor. Finally, Section V concludes.

I. Data and Measurement

We measure a firm’s labor exposure to Generative AI in two steps. First, we measure each *occupation’s* exposure to Generative AI based on the occupation’s task statements from the O*NET database. Second, we aggregate the occupation-level Generative AI exposure measure to the firm level using the firm-occupational employment data from the Revelio Labs Workforce Dynamics database.

A. Measuring occupational exposure to Generative AI

Occupational task data To assess an occupation’s exposure to the impact of Generative AI models, we use a task-based approach. That is, we consider an occupation to be a set of tasks-to-be-done and evaluate whether each task can be done more productively using ChatGPT and similar large language models (LLMs) or future applications that will be built based on their capabilities.

We obtain information on the tasks involved in each occupation from the O*NET V27.2 database, which provides a list of task statements created by practitioners or occupational

⁹Indeed, as we draft this study, IBM, the company ranked #1 in our exposure to Generative AI measure among the largest U.S. firms announced to halt hiring of 7,800 jobs that could be replaced by AI. See <https://www.businessinsider.com/ibm-halts-hiring-for-7800-jobs-that-could-be-replaced-by-ai-report-2023-5>

experts.¹⁰ A task statement is usually one sentence, and an occupation has on average 22 tasks. The 19,265 pairs of task statements and the occupations that they belong to then need to be coded as being exposed to Generative AI technologies or not.

Task scoring We score tasks’ exposure to Generative AI following the approach that was suggested and validated by Eloundou et al. (2023). In particular, we use GPT itself to score exposure of tasks based on whether the task can already be done directly using the ChatGPT interface, or can be done with additional tools built on top of it. Two advantages of using an LLM instead of human to assess task statements are that it allows for better replicability of the research in terms of cost and speed of execution, and rapid scaling of the method to the full set of 19,265 task statements.¹¹

Specifically, we use Open AI’s GPT 3.5 Turbo model to classify the full set of task statements and validate its reliability on a smaller subsample of tasks.¹² The model is given an overall rubric for scoring LLM exposure, as well as two example interactions between a user and an assistant that showcase the kind of output it is expected to produce. Then, a task statement is submitted together with its O*NET occupation title, and the model returns a score. The scores indicate whether ChatGPT-like tools can shorten the time to complete the task by at least half for the same quality as human completion. The scores fall into the following categories: *E0* indicates no exposure as the tool is either insufficiently useful for this task, or cannot be brought to bear as a result of the intrinsic nature of the task, e.g. if it involves physical activities; *E1* is applied if a 50% reduction in completion time is already feasible with the existing large language model interfaces; and *E2* requires that such a productivity gain is feasible, but only when the current capabilities of the model can be deployed through applications with further inputs (e.g., access to Internet or proprietary databases), or if it is trained on domain-specific issues or data. Importantly, the model is asked not only to respond with the score but also to explain its reasoning, which allows researchers to audit whether GPT is in fact understanding the prompt as intended and interpreting the task correctly. This auditing capability is another advantage of LLMs as it

¹⁰This data can be accessed via the O*NET website at <https://www.onetonline.org>

¹¹While similar large-volume classification tasks in the past often relied on crowd-workers on online platforms such as Amazon Mechanical Turk (MTurk), ChatGPT has recently been shown to outperform human crowd-workers in accuracy in text classification tasks, while also exhibiting lower variability in scores across multiple runs of the program (Gilardi, Alizadeh, and Kubli, 2023). Economists have also recently used other large language models to classify unstructured text from job postings and found that they outperformed other machine learning methods Hansen, Lambert, Bloom, Davis, Sadun, and Taska (2023).

¹²The structure of the prompt submitted to the Open AI GPT API is shown in Appendix A. See also Lopez-Lira and Tang (2023) for using ChatGPT to extract sentiment from news headlines and predict stock returns.

is oftentimes unavailable in instances of human text classifications.¹³ A random sample of scored tasks together with the model’s explanations can be found in Appendix Table C1.

Scoring occupations’ exposure to Generative AI We next aggregate tasks’ exposure to Generative AI to the occupation level. For each 8-digit Standard Occupational Classification (SOC) occupation from the O*NET, we calculate the share of the total number of tasks for each occupation that are affected by Generative AI. We follow Eloundou et al. (2023) and focus on an aggregation that takes into account that scores of 1 represent the current direct feasibility of productivity improvements, while exposure scores of 2 rely on investment in additional capabilities, such as interaction through custom-built applications or the ability to search local or online databases, that complement the current LLM chat interface. Therefore, our main measure of the share of an occupation o ’s exposed tasks counts both the number of tasks with exposure rubric 1 (N_1) and those with exposure rubric 2 (N_2) but applies half the weight to the latter. That is, our exposure score at the occupation level for each occupation o is:

$$E_o = \frac{N_1 + 0.5 * N_2}{N_0 + N_1 + N_2}.$$

Finally, we aggregate across 8-digit O*Net occupation codes to the 6-digit SOC level to match the occupation-level exposure measure to firms’ occupational data. Note that the Generative AI exposure measure is bounded by 100% on the upper end, representing that all tasks in that occupation can be done at least 50%

The full set of 6-digit occupations for which we compute Generative AI exposures consists of 778 occupations, of which 678 are also contained in the firm-level employment structure data described below. The mean and median exposure in the latter set of occupations are 23% and 18%, respectively, with a standard deviation of 21 ppt. The inter-quartile range extends from 6% to 38% exposure. Appendix Table C3 shows an overview of the 20 occupations with the highest and lowest Generative AI exposure scores.¹⁴ Note that among the highest exposure occupations, many, such as “Telemarketers”, “Computer programmers”, and “Interpreters and translators”, map closely onto some of the key recent technological advances in Generative AI regarding its ability to hold natural text-based conversations, generate functioning code based on high-level descriptions of a programming task, and translate texts accurately between languages and styles.¹⁵

¹³The model was also asked to return a confidence score (low/medium/high) for its prediction, but while this may have led the LLM to focus on refining its answer in this regard, we do not use this dimension of the response. In most cases, the model expresses “high confidence” in its assessment.

¹⁴Note that the lowest score category only shows a subset of a larger set of occupations with zero Generative AI exposure.

¹⁵While “Mathematicians” might seem out-of-place among occupations with high exposure to Generative

Occupations’ exposure to Generative AI differs substantially from their exposure to automated studied in the prior literature. Acemoglu and Autor (2011) summarize the literature and characterize occupations’ skills by routine vs. non-routine, cognitive vs. manual, and analytical vs. interpersonal aspects. To understand how their categories map onto occupations’ exposure to ChatGPT-like technologies, we regress our 6-digit occupation Generative AI exposure measure on the set of occupational skill scores defined by Acemoglu and Autor (2011). Specifically, we run the following regression:

$$E_o = \alpha + \sum_s \beta_s * Skill_{s,o} + \varepsilon_o.$$

Figure 2 shows the results. We find that occupations with higher Generative AI exposure are more likely to involve non-routine cognitive analytical skills or routine cognitive skills, and less likely to involve different kinds of manual skills, or interpersonal skills. These results demonstrate the unique features of Generative AI’s disruption to firms’ employees. The literature on previous waves of automation shows that the technology displaces routine-task jobs (i.e., repetitive and codifiable tasks) and complements cognitive-task jobs ((Autor et al., 2003)).

Different from computers, tools like ChatGPT can interpret and respond to relatively unstructured inputs, display a surprising amount of common sense in filling in gaps in instructions, and can respond with relatively complex outputs, such as texts in different styles, or – in the case of image generators like Stable Diffusion or Midjourney—even with new and original images (Bubeck, Chandrasekaran, Eldan, Gehrke, Horvitz, Kamar, Lee, Lee, Li, Lundberg, et al., 2023). As a result, this wave of technological change may differ from previous waves in that many tasks in non-routine cognitive analytical jobs that were safe from automation by previous technologies are now suddenly more likely to be substituted for by software and computers.¹⁶

AI, note that Fields Medal winner Terence Tao of UCLA remarked in April 2023, that “GPT-4 has saved [him] a significant amount of tedious work”, noting that “while these AI tools do not directly assist [him] in core tasks such as trying to attack an unsolved mathematical problem, they are quite useful for a wide variety of peripheral (but still work-related) tasks (though often with some manual tweaking afterward).” (Source: <https://pandaily.com/mathematician-terence-tao-comments-on-chatgpt/>)

¹⁶To better understand which occupation characteristics are associated with higher exposure, Panel A of Appendix Figure B1 shows the relationship between the average wage level of each 2-digit major occupation group in 2021 and our estimated Generative AI exposure. As the graph shows, higher-wage occupations are generally more likely to be exposed to ChatGPT-like technological advances making their constituent tasks more productive. One notable exception is the relatively low-wage “Office and Administrative Support” occupations, which are also predicted to be highly exposed. The positive relation between Generative AI exposure and wage is also observed at the industry level. In Panel B of Appendix Figure B1, we aggregate occupational Generative AI exposure and occupational wages to the NAICS 2-digit industry level using the 2021 BLS National Employment Matrix. We observe a similar pattern that high-wage industries also tend

B. Measuring firms’ exposure to Generative AI

To estimate a firm’s exposure to Generative AI, we use data on firms’ occupational structure to aggregate our occupational exposure measure. We obtain data on firms’ occupational employment from Revelio Labs, which collects information on job titles and employers from LinkedIn and other resume profiles and constructs occupation-by-firm employment counts. Our customized data define a firm at the unique Compustat identifier *gvkey* and define an occupation using the 6-digit SOC. We use the employment counts for each *gvkey*-SOC6 as of March 2022, which is the latest month in our data.

We construct a firm’s Generative AI exposure as the weighted average of its occupations’ Generative AI exposure, using the firm’s occupational employment as weights. That is,

$$E_f = \sum_{\text{occupations in } f} EmpShare_{f,o} * E_o,$$

where $EmpShare_{f,o} = \frac{emp_{f,o}}{emp_f}$ is the employment share of occupation *o* in firm *f*. The result of this procedure is a cross-section of 2,518 publicly-traded firms with predicted exposure to Generative AI and basic company characteristics from Compustat.

C. Summary statistics of firms’ Generative AI exposure

Table I shows the summary statistics of our sample which includes 2,518 publicly traded firms in the cross-section of 2022. On average, the firms in our sample have a mean and median task exposure score of 35%, with a standard deviation of 8 ppt. The firm-level measure of exposure to Generative AI spans from 27% at the 10th percentile to 44% at the 90th percentile.

Table II lists the 15 firms with the highest and lowest exposure to Generative AI, respectively, among the top 100 largest U.S. firms by market capitalization in 2022. While many IT firms, such as IBM and Intuit, not surprisingly have a large fraction of employees exposed to Generative AI, we also observe manufacturing firms, such as 3M, and administrative conglomerates, such as S&P Global, in this high-exposure category. The large U.S. firms ranked at the bottom of the exposure distribution include restaurants, such as Starbucks and McDonald’s, retail firms, such as Target and Walmart, transportation firms, such as UPS, and manufacturing firms, such as Tesla, suggesting that they have a smaller fraction of employees exposed to Generative AI.

Perhaps surprisingly, Figure 3 shows that the variation in firm-level exposure to Generative AI has a significant within-industry component. While industry sectors such as “Infor-

to have high exposure to Generative AI.

mation” and “Professional, Scientific, and Technical Services” have an average firm exposure to Generative AI of about 13% greater than industries such as “Accommodation and Food Services,” there are substantial variations of firms’ exposure to GPT within each industry. A variance decomposition shows that industry differences explain only 18% of the firm-level variation in exposure to Generative AI. The rich within-industry variations in firms’ exposure to Generative AI motivate us to explore our firm-level empirical analyses within industries. Importantly, the within-industry analyses distinguish our labor-based mechanism from the explanations based on products’ exposure to Generative AI when studying the effects of firms’ exposure to Generative AI on firm values.

How do firms’ exposure to Generative AI relate to other firm characteristics? Panel A of Table III shows that firms with higher exposure to Generative AI tend to be smaller, have greater Tobin’s Q, and are less profitable. These findings are consistent with the notion that such small and high-growth firms tend to focus their workforce on cognitive tasks. Moreover, we also observe that firms with higher labor intensity, higher organizational capital ratio (Eisfeldt and Papanikolaou, 2013) and less tangible capital are more exposed to Generative AI. We will thus control for these firm characteristics in our later analyses. Panel B of Table III shows that the above associations between firms’ Generative AI exposure and firm characteristics are mainly a cross-industry feature but not within-industry, except for the associations with labor intensity and asset tangibility. Hence, other firm characteristics may cast a less confounding concern for our within-industry analyses later.

II. Stock Market Impact of Generative AI Exposure

A. *Realized returns and Generative AI exposure*

We identify the impact of Generative AI on firm value via the differential stock returns for firms with high and low Generative AI exposure during the ChatGPT impact period and during other periods. While a positive cross-sectional return spread during the ChatGPT impact period shows the effect of the Generative AI shock on firm value, the return spread during the non-impact period examines the innate differences in firm returns absent the Generative AI shock.

Defining the ChatGPT “event” period ChatGPT was released on November 30, 2022. We show in Section III that the release immediately amassed considerable attention from the general public as well as investors in the next two weeks. We define the “ChatGPT release period” consisting of November 30, 2022 and the following two weeks until December 14,

2022 in our analyses. We define the rest of the days from November 15, 2022 to March 31, 2023 as the “Not ChatGPT release period”. Figure 4 shows that volatility spiked on the release date (Panel A), while Twitter mentions climbed subsequently, peaking about a week after the release. We choose a two-week window as a balance between allowing enough time for information to be digested and incorporated while not allowing so much time that other shocks affecting firm values become too much of a confounding factor.

Forming Generative AI exposure portfolios To estimate whether Generative AI exposure affects the realized returns of stocks during the event window, we first form value-weighted high and low exposure quintile portfolios, and also a high-minus-low portfolio—which we refer to as the “Artificial Minus Human” (*AMH*) portfolio—that represents the zero net investment portfolio long high exposure (*H*) stocks and short low exposure (*L*) stocks. In particular, at the beginning of our sample period, we sort stocks traded on the NYSE exchange into five quintiles based on their Generative AI exposure, and we use the NYSE breakpoints to assign non-NYSE stocks into the quintile bins. We compute the value-weighted daily returns of each portfolio as the average daily returns of stocks in the portfolio weighted by their previous day’s market capitalization.¹⁷

Portfolio sorting results Panel A of Table IV shows the mean excess realized returns of the quintile portfolios sorted by firms’ Generative AI exposure and also the long-short AMH portfolio during the “ChatGPT release period” and the “Not ChatGPT release period.” We observe that the *AMH* high-minus-low exposure portfolio has positive daily returns of 0.43% (t -statistic = 3.54) on average during the two weeks post-ChatGPT release. However, outside this ChatGPT release period, we observe a negligible average return of 0.008% for the AMH portfolio. AMH portfolio’s average return during the ChatGPT release period is also statistically different from its average return outside the period. This key finding—that companies with higher employee exposure to Generative AI show significantly higher average returns only during periods when advances in large language model technology became known but not in other periods—helps quantify the impact of Generative AI breakthroughs on firm value.

In Panel B of Table IV, we additionally control for each portfolio’s exposure to the market factor by reporting the constant coefficient, alpha, of regressing the portfolio’s excess daily returns on the market returns. The market adjusted alpha of the AMH portfolio shows very similar results as the returns of the AMH portfolio, suggesting that our main finding is not driven by firms’ heterogeneous exposure to the market. In Panel C, we further

¹⁷See Appendix Section A for more details on the portfolio construction.

consider whether the excess returns on the Generative AI-exposed stocks after the release of ChatGPT can be explained by an association between this exposure and other risk factors. We construct the alphas of each portfolio using the Fama-French 5-factor model (Fama and French (2015)). Again, we observe similar results: the AMH portfolio’s 5-factor adjusted alpha is 0.31% during the ChatGPT release period but -0.03% outside this period, and the difference between the two periods is statistically significant.

Time series of Generative AI exposure portfolio returns To further visualize that the Generative AI exposure returns are associated with the advances in the related technology, we plot the time series of daily excess returns of the top and bottom quintile portfolios and also the AMH long-short portfolio in Figure 1. We observe that while the firms with low exposure to Generative AI dropped by 4% during the ChatGPT release period, from December 1, 2022 to December 15, 2022, firms with high exposure to Generative AI see a rise in excess returns of about 2% in this period. Put together, the AMH long-short portfolio seems a positive 6% cumulative return in the ChatGPT release period. We note that the overall market actually fell during this two-week window.¹⁸ We extend the cumulative returns to the end of our sample and observe that the positive cumulative return of the AMH portfolio is sustained following the ChatGPT release period and reaches about 7% on March 31, 2023.

B. Importance of within-industry heterogeneity

We have shown earlier in Figure 3 that firms’ exposure to Generative AI varies substantially within-industry. In this section, we examine to what extent the AMH returns during the ChatGPT release period are driven by within-industry variation. An important message of the within-industry analyses is to dissect whether firms’ Generative AI exposure measures firms’ employees’ exposure to ChatGPT disruption or proxies for firms’ products’ exposure to ChatGPT disruption. While both channels are interesting, distinguishing the two helps understand the mechanism driving the AMH portfolio’s high returns during the ChatGPT release period.

Given the limited number of stocks within an industry, we form three tercile portfolios (instead of quintile portfolios) within each industry, and then value-weight stock returns in the industry-neutral tercile portfolios. We consider two industry classifications. On the one

¹⁸The S&P 500 index dropped by 4.4% from December 1, 2022 to December 15, 2022. See <https://www.google.com/finance/quote/.INX:INDEXSP?sa=X&sqi=2&ved=2ahUKEwiruL6e0fuAAxXGh-4BHW5MCd8Q3ecFegQILRAf&window=1>. Note that the overall market includes the middle two AMH terciles, so A and H do not aggregate to the market.

hand, we use the NAICS 3-digit industry classification, which includes 46 categories with at least 10 firms in our data. On the other hand, Hoberg and Phillips (2016) show that the rich text of firms’ descriptions of their products in their 10K filings can more precisely separate product markets. We thus also adopt the 10K-based FIC50 industry classification as an alternative measure of industries.

Table V shows the results. Panel A1 shows the market adjusted alphas for the tercile portfolios sorted by firms’ Generative AI exposure as the benchmark. Panels A2 and A3 show the market adjusted alphas for the industry-neutral tercile portfolios using the NAICS 3-digit industry classification and the FIC50 industry classification, respectively. In all three panels, we observe that the within-industry AMH portfolio has large and statistically significant alphas during the ChatGPT release period and small and negative alphas outside the period. More importantly, the AMH alphas are very similar whether we use the full cross-sectional variation or only within-industry variation in firms’ Generative AI exposure. Panels B1-B3 show a very similar result when we examine the FF5-factor adjusted alphas instead of the market adjusted alphas. If industry classifications capture the effects of improvements to Generative AI on the demand for firms’ products, then the within-industry findings suggest that a substantial portion of the positive effects of the Generative AI breakthrough on firm value are due to the technology’s impact on firms’ labor rather than on firms’ products. This interpretation may provide further support for our labor-task-based measure of firms’ Generative AI exposure. In later sections, we dig deeper into the labor mechanism.

To further investigate how much tech firms, in particular, are driving our main findings, we follow Acemoglu, Autor, Hazell, and Restrepo (2022) and single out firms in two sectors (information sector (NAICS 51) and professional, scientific, and technical services sector (NAICS 54)) as tech firms whose outputs are especially affected by the release of ChatGPT. Note that we do not claim that the ChatGPT release does not impact firms’ products and services. Instead, our goal is to provide support for the idea that the differential returns we document for firms with different labor-force exposures to Generative AI are indeed driven by the labor channel. Labor and product market channels are not mutually exclusive. In Panel D of Table IV, we redo our main quintile sorting analyses but exclude firms from the two tech sectors. We observe very similar results. The FF 5-factor adjusted alphas for the AMH portfolio using non-tech firms has an average daily return of 0.33% during the ChatGPT release period as compared to 0.31% using all firms. In Appendix Figure B2 we show the AMH portfolio returns during the ChatGPT release period for each NAICS 2-digit sector. We observe that positive significant AMH portfolio returns are mainly driven by sectors such as manufacturing, finance, mining, health care, administrative, etc., and *not* by the information or professional sectors. While this may seem surprising, note that these

figures report AMH returns within industry, so the overall return to the tech sector during the release period can still be large.

C. *Firm characteristics and returns to Generative AI exposure*

We next investigate whether our finding of increased value for companies with greater task-based exposure to Generative AI is confounded by our measure’s correlation with other firm characteristics. In this section, we run a horse race test using the following regression specification:

$$\begin{aligned} r_{it} - r_t^f &= \beta_1 \mathbb{1}[\text{Release Period}]_t \times \text{High GenAI Exposure}_i \\ &+ \beta_2 \mathbb{1}[\text{Release Period}]_t \times \text{Firm Char}_i \\ &+ \beta_3 \text{GenAI Exposure}_i + \beta_4 \text{Firm Char}_i + FEs + \varepsilon_{it}, \end{aligned}$$

where *High GenAI Exposure_i* is a dummy variable indicating that firm *i*’s Generative AI exposure is above the top decile breakpoint sorted using the NYSE stocks, β_1 measures the impact of ChatGPT release on firms with high Generative AI exposure relative to other firms, β_2 measures the impact on firms with other characteristics, and *FEs* represents trading day fixed effects and NAICS 3-digit industry fixed effects.

Table VI shows the results. Column (1) shows that firms with higher Generative AI exposure experience greater stock returns during the GPT release period than other periods, consistent with our portfolio sorting results. Columns (2)-(8) show that the above main finding is robust to controlling for firms’ affiliation with the tech sector and various firm characteristics, including firm size, Tobin’s Q, ROA, labor intensity, organizational capital ratio, and asset tangibility. In Column (9), we include all firm characteristics in one regression and observe that our main finding remains. In summary, this analysis suggests that our main findings based on firms’ exposure to Generative AI are not confounded by firms’ other characteristics.

III. Investor Attention and Generative AI Exposure

Historically, understanding the impact of new technologies on businesses is a progressive and slow process. A strand of literature on the slow diffusion of technology shows that technological diffusion is subject to various frictions, including limited attention of firms to the new technology or firms’ unwillingness to employ the new technology (Greenwood

(1999)).¹⁹ Indeed, these papers show that it can take a long time for new technologies to have a widespread impact on production. As a result, many studies on the impact of technology are retrospective rather than occurring soon after the arrival of the technology.²⁰

The release of ChatGPT rapidly garnered massive attention, potentially overcoming the information hurdles for past technologies.²¹ As a result, this setting potentially offers an insight into the impact of a technology shock in “real time”. In addition, the fast spread of ChatGPT news and applications helps answer a crucial plausibility question about our main stock return findings: Can the stock market quickly pick up the impact of Generative AI on firms within weeks, as we argue? A key to answering this question is whether ChatGPT raises investors’ attention in our ChatGPT release period. In this section, we provide supporting evidence that ChatGPT, unlike prior technologies, quickly grabbed the attention of the general public. More importantly, the impact of the awareness by investors and firm executives appears disproportionately greater for firms with greater exposure to Generative AI.

A. Public attention from Twitter mentions of GPT

We begin by showing that the release of ChatGPT has garnered massive public awareness. Figure 4 shows that immediately after the release of ChatGPT on November 30, 2022, the Twitter mentions of “ChatGPT” or “GPT” reached over 100K daily. Mentions remain at 50K mentions daily even two weeks after the release.

B. Stock volatility and firm Generative AI exposure

We hypothesize that, if investors are plausibly aware that ChatGPT may affect firms more exposed to Generative AI, these stocks should be more volatile because the market must impound a large and complex information shock.

We use the volatility of stocks’ daily returns to proxy for investors’ incorporation of the ChatGPT release news into stock prices.

In particular, we regress the absolute value of firms’ absolute value of daily stock returns

¹⁹For instance, the average time length for a new technological product to diffuse from 10% to 90% (of the full adoption level) is over 10 years (see many examples in Greenwood (1999) and Manuelli and Seshadri (2014)).

²⁰For instance, the seminal work studying the impact of computer-based automation on the labor market since 1980 is Autor et al. (2003).

²¹For instance, ChatGPT amassed 100 million users in just two months after its release, a milestone which took World Wide Web 7 years, WhatsApp 3.5 years, Instagram 2.5 years, and Twitter 5 years to reach. See <https://economictimes.indiatimes.com/news/new-updates/chatgpt-witnesses-massive-rise-chatbot-gains-100-million-users-in-two-months/articleshow/98428443.cms?from=mdr>.

on their exposure to Generative AI. In Figure 4, we run the following regression on each day and show the t-statistic for the hypothesis $\beta_t = 0$:

$$|r|_{it} = \alpha_t + \beta_t \text{GenAIExposure}_i + \varepsilon_{it},$$

This regression is estimated at the firm level, for each trading day from Nov. 15, 2022, to Dec 14, 2023 (two weeks before and after the release of ChatGPT).

The figure confirms that the days on which our firm employment-structure based measure of Generative AI exposure predicts higher stock return volatility around the release of ChatGPT closely coincide with surging social media attention to the technology. The fact that the volatility impact of our Generative AI exposure measure reliably identifies the key period when major related news was released validates that it captures a dimension of exposure to the associated technologies that are relevant to market participants.

C. Firm earnings conference call mentions of Generative AI

We next examine whether firms’ awareness of Generative AI’s impact is aligned with our measure of their exposure to Generative AI. We manually collect from the Seeking Alpha website a panel of the earnings conference call transcripts for S&P 500 firms from July 2018 to March 2023. For each of these earnings calls, we assign a calendar month, quarter, and year (as distinct from the fiscal year and quarter referenced in the call), based on the time stamp of the earnings call transcript. We process each transcript by converting it into a list of lower-case tokens, creating separate lists of unigrams (one-word tokens) and bigrams (two-word tokens).

We define a transcript as mentioning the Generative AI topic if it mentions the following keywords: “llm”, “chatgpt”, “gpt”, “gpt3”, “gpt4”, “generative”, or “language model”. For comparison, we define a transcript as mentioning the machine learning-related topic that is not specific to Generative AI technologies if it mentions “ml”, “machine learning”, “deep learning”, “natural language”, “neural net”, “neural network”, or “nlp”; and we define a transcript as mentioning the engineering topic if it mentions “engineer” or “engineering”.

Figure 5 shows that the share of firms mentioning Generative AI in their quarterly earnings calls rose substantially after ChatGPT’s release from less than 5% to 27%. In contrast, the percentage of firms mentioning machine learning or engineering does not show such up-rise patterns after ChatGPT’s release.

Is the increase in firms’ mentions Generative AI disproportionately more prominent among firms with higher Generative AI exposure? To answer this question, we run the

following regression in each quarter:

$$\mathbb{1}[\text{Topic } X]_{it} = \alpha_t + \beta_t^X \text{GenAI Exposure}_i + \gamma \mathbb{1}[\text{Topic } X]_{i,2019} + \varepsilon_{it}, \quad (1)$$

where β_t^X represents the association between firms' mentioning of topic X in quarter t and their exposure to Generative AI, while controlling for the firms' past mentioning of the topic in 2019. A positive association between firms' awareness of Generative AI and our measure of firms' exposure to Generative AI provides additional support for our labor-exposure measure.

Figure 6 shows the results. In Panel A, we observe that firms more exposed to Generative AI, as suggested by our measure, see a substantially stronger increase in mentions of Generative AI after ChatGPT's release. In contrast, we do not observe a strengthened association of firms' mentions of non-Generative AI-related machine learning topics or engineering topics with firms' exposure to Generative AI after ChatGPT's release, as shown in Panels B and C of Figure 6.

In summary, the massive rise in public and corporate attention to ChatGPT after November 30, 2022, combined with the disproportionately greater reactions to firms with higher Generative AI exposure, brings two important validation messages to our analyses. First, these findings reveal that the breakthrough of Generative AI, highlighted by the launch of ChatGPT, attracted attention from investors more rapidly than was the case for the prior major technology breakthroughs. The swift and substantial attraction of investor attention makes detecting stock return responses to the launch of ChatGPT upon its release plausible. Second, the stronger reactions by investors and firms among firms with higher labor-based exposure to Generative AI supports sorting by firms' labor exposure to Generative AI to measure the impact of Generative AI on firm values.

IV. Generative AI: Labor Complement or Substitute?

Generative AI may affect firms' exposed employees in at least two ways. First, firms whose labor force can be substituted for with cheaper Generative AI-based capital will experience higher free cash flows by lowering input costs.²² We call this a *labor-substitution* mechanism. Second, firms whose labor inputs are more complementary to Generative AI will experience higher cash flows due to the technological improvement in an input that is complementary to their workforce.²³ We call this a *labor-complementarity* mechanism. While both mechanisms may increase firms' free cash flows in the future and thus increase firms' values, identifying

²²See Autor et al. (2003) and Zhang (2019) for measures of firm exposure to automation and Webb (2019) and Lane and Saint-Martin (2021) for the impact of AI on firms.

²³See Krusell et al. (2000) and Eisfeldt et al. (2022).

the mechanism not only helps us understand the underlying machinery for our stock return results but also helps us understand Generative AI’s impact on firms’ labor.

We use the most recent Lightcast (formerly Burning Glass) data on firm job postings to shed light on firms’ demand for various types of skilled labor. From the Lightcast data, we construct firms’ number of job postings for each occupation in each month from January 2010 to July 2023. We focus on changes in firms’ job posting patterns for occupations highly exposed to Generative AI according to our classification in Section I.A. In particular, we define occupations in the top decile ranking by Generative AI exposure as the *High GenAI Exposure* occupations. We next define all months after November 2022 as the *Post-ChatGPT* period and the earlier periods as the pre-ChatGPT period.

We hypothesize that if our stock return findings are driven by Generative AI complementing exposed occupations, we should expect an *increased* demand for Generative AI exposed occupations, especially by firms with high Generative AI exposure. If our stock return findings are driven by Generative AI substituting exposed occupations, we should expect a *decreased* demand for Generative AI exposed occupations, especially among firms with high Generative AI exposure. We test our hypothesis by estimating a difference-in-differences regression as follows:

$$\text{Job Posting}_{it} = \alpha_i + \alpha_t + \beta \mathbb{1}[\text{Post-ChatGPT}]_t \times \text{GenAI Exposure}_i + \varepsilon_{it},$$

where *Job Posting_{it}* represents firm *i*’s job posting of *High GenAI Exposure* occupations or its total job posting numbers.

Panel A of Table VII reports the estimates of β . Columns (1) and (2) show that firms with higher Generative AI exposure post fewer total jobs and also fewer jobs with high Generative AI exposure after the release of ChatGPT. This finding supports Generative AI being an overall substitute for labor, rather than complementary to it.²⁴ Panel B reinforces this conclusion by investigating the *share* of job postings for occupations highly exposed to Generative AI to all job postings and showing that firms with higher Generative AI exposure especially reduce demand for high Generative AI exposed jobs after ChatGPT’s release.

We strengthen our findings on the labor-substitution mechanism by further investigating firms’ demand for AI-related skills. Specifically, the labor-substitution mechanism suggests that firms with higher Generative AI exposure use the new technology to displace jobs that are highly exposed to Generative AI. While we do not yet have data on firms’ adoption of Generative AI technology, one may assume that such adoption is likely accompanied by

²⁴While it is possible that labor’s share increases even when employment or hours declines if compensation increases enough we do not view this as particularly plausible. However, we acknowledge that not having wage and hours data is a limitation to our inference.

firms hiring employees with high AI skills. Indeed, Table VII shows that while firms with higher Generative AI exposure reduce their overall job postings (Column (1) of Panel A), they do not reduce their job postings for AI skills (Column (3) of Panel A), resulting in a substantial increase in these firms share of job posting for AI skills (Column (3) of Panel B). In summary, these changes reflect a greater shift in labor composition away from highly Generative AI exposed occupations and towards AI skills among firms with higher exposure to Generative AI. This shift supports the labor-substitution mechanism.

V. Conclusion

Market prices indicate that the arrival and diffusion of large language models and Generative AI represent a major technology shock with important effects on the overall value of firms, as well leading to winners and losers. This paper uses occupational exposures to Generative AI, along with firm-level measures of occupational composition, to assess the exposure to Generative AI innovations at the firm level for publicly traded U.S. corporations. We find that the effect of the release of ChatGPT on firm values was large, driving a difference in firm returns of approximately .4% daily, translating to over 100% on an annualized basis. These differences were realized both within and across industries, and display wide variation which is correlated with firm characteristics such as organizational capital or gross profitability. According to investors, ChatGPT represents an important shock to corporate valuations.

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Figure 2: Occupational skills and Generative AI exposure. The graph below shows the results of regressing our 6-digit occupation’s Generative AI exposure measure jointly on a set of occupational skill scores defined in Acemoglu and Autor (2011), converted into standard z-scores. That is, we run the following regression:

$$\text{Exposure}_o^{GPT} = \alpha + \sum_s \beta_s \text{Skill}_o + \varepsilon_o$$

The regression sample contains 690 occupations. The bars around each coefficient show 95% confidence intervals based on heteroskedasticity-robust standard errors.

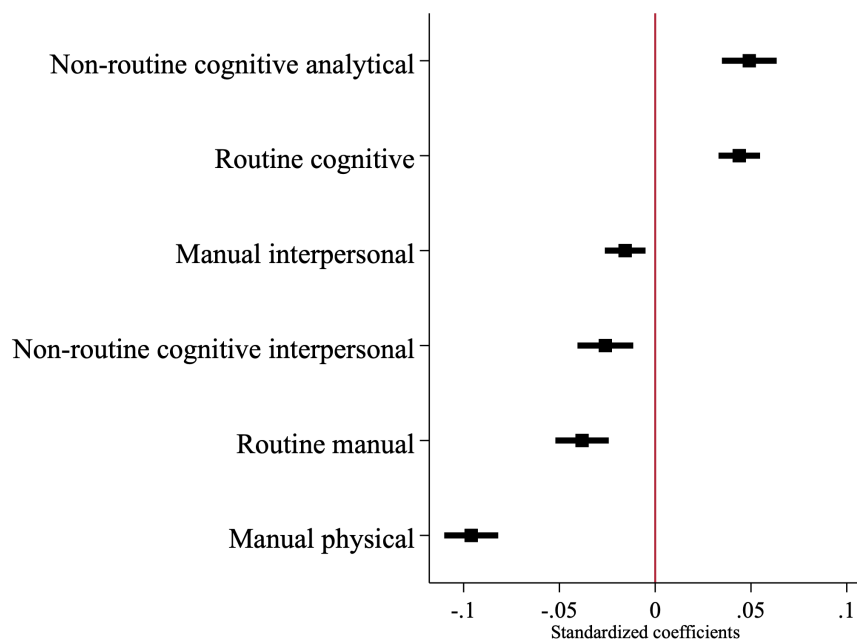


Figure 3: Generative AI exposure across and within sectors. This figure plots the average and the standard deviation of Compustat firms' Generative AI exposure within each NAICS 2-digit sector.

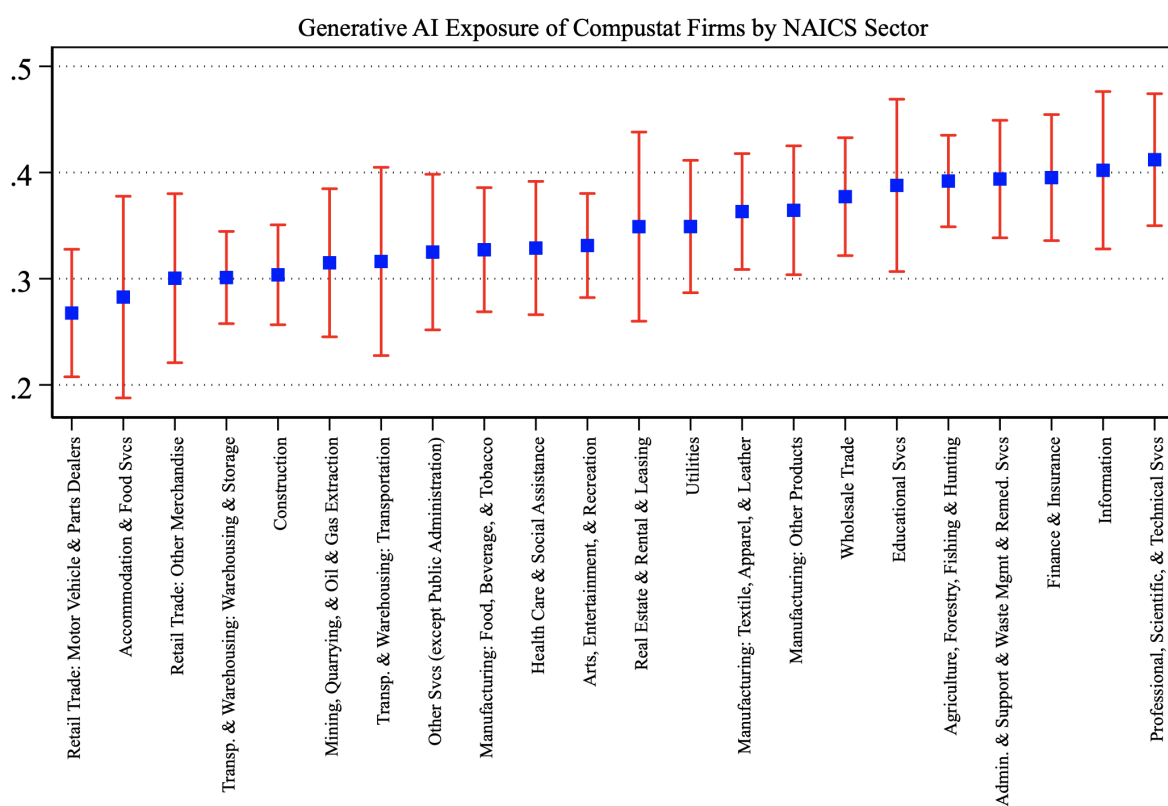
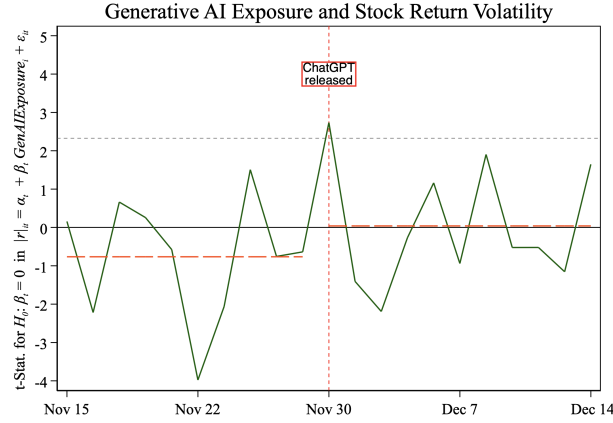
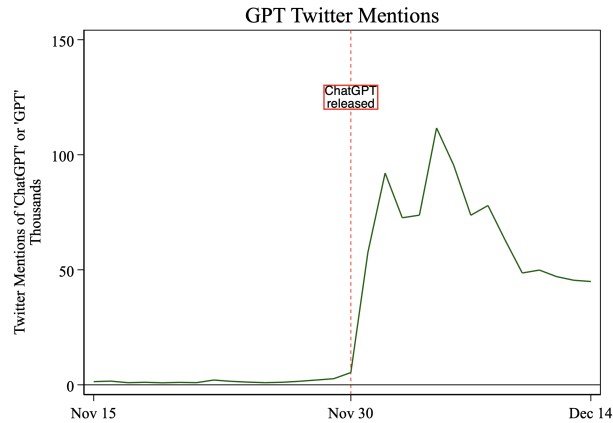


Figure 4: Stock return volatility, Generative AI exposure, and social media attention. Panel A shows the t-statistic for the hypothesis $\beta_t = 0$ in the regression $|r|_{it} = \alpha_t + \beta_t \text{GenAIExposure}_i + \varepsilon_{it}$, estimated at the firm level, for each trading day from Nov. 15, 2022, to Dec 14, 2023 (two weeks before and after the release of ChatGPT). The dependent variable in the regression is the absolute value of daily stock returns, and the independent variable is the firm-level measure of task exposure to Generative AI technology productivity changes. Standard errors are heteroskedasticity-robust. The dashed horizontal line indicates where t-statistics exceed 2.326 (p-value < 0.01.). Orange dashed lines indicate the mean t-statistic in the two weeks pre- and post-ChatGPT. Panel B shows the total count of Twitter mentions of “ChatGPT” or “GPT” reported by Media Cloud.

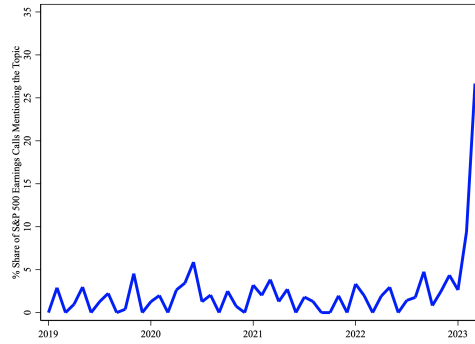


(A) Stock return volatility and firm Generative AI exposure

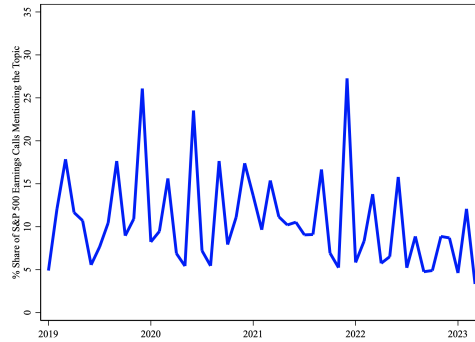


(B) Twitter mentions of GPT and firm Generative AI exposure

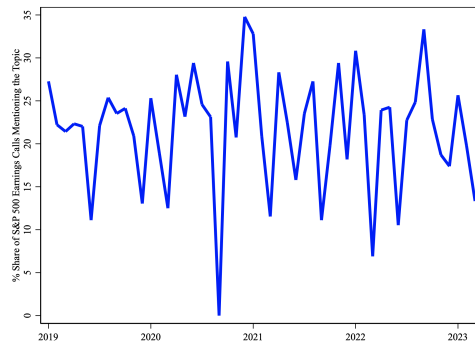
Figure 5: Topic mentions in company earnings conference calls. This figure shows the share of S&P 500 firms’ earnings calls that mention each topic. The quarterly earnings conference call transcripts for S&P 500 firms’ are manually collected from the *Seeking Alpha* website. Panel A shows the share of earnings calls mentioning Generative AI keywords: “llm”, “chatgpt”, “gpt”, “gpt3”, “gpt4”, “generative” and “language model”. Panel B shows the share of earnings calls mentioning keywords of machine learning, deep learning or natural language processing: “ml”, “machine learning”, “deep learning”, “natural language”, “neural net”, “neural network” and “nlp”. Panel C shows the share of earnings calls mentioning keywords about engineering: “engineer” and “engineering”. See Section I for more details of our data collection and variable construction.



(A) Share of earnings calls mentioning Generative AI



(B) Share of earnings calls mentioning ML/DL/NLP

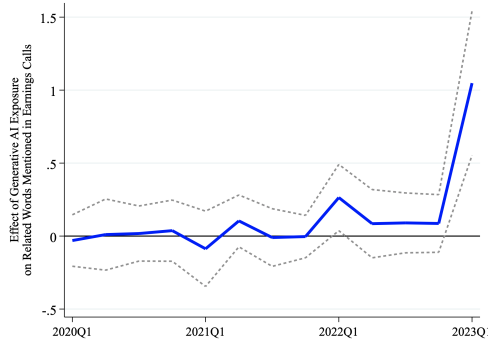


(C) Share of earnings calls mentioning Engineering

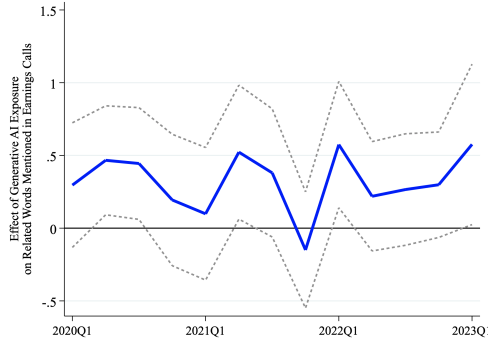
Figure 6: Firm-level Generative AI exposure and topics in company earnings conference calls. Each graph show the result of estimating regression specifications of the form

$$\mathbb{1}[\text{Topic X}]_{i,t} = \alpha_t + \beta_t^X E_i^f + \gamma \mathbb{1}[\text{Topic X}]_{i,2019} + \varepsilon_{i,t}$$

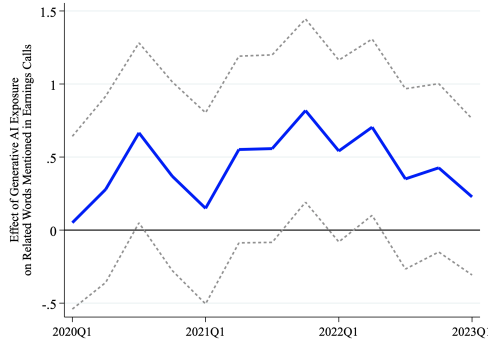
for each topic for the fiscal quarters 2019 Q1-2023 Q1 for a manually collected panel of quarterly earnings conference call transcripts for S&P 500 firms' tickers from the *Seeking Alpha* website. Each call transcript is converted into a list of lower-case unigrams and bigrams. See Table 5 for keywords about Generative AI topic, ML/DL/NLP topic, and Engineering topic. Dotted lines show 95% confidence intervals based on heteroskedasticity-robust standard errors.



(A) Firm mentioning Generative AI and firm Generative AI exposure



(B) Firm mentioning ML/DL/NLP and firm Generative AI exposure



(C) Firm mentioning Engineering and firm Generative AI exposure

Table I: Summary statistics for selected firm characteristics. *Generative AI exposure* is our bottom-up task-based measure of occupational exposure, aggregated to the firm-level based on the firm’s occupational employment structure. *Log Size* is the natural logarithm of total assets. *Labor Intensity* is the logarithm of the ratio of Property, Plant & Equipment (PP&E) to Total Assets, based on Donangelo (2014). *Tangibility* is the ratio of PP& E to Total Assets. *Org. Capital Ratio* is the ratio of the organizational capital stock from Eisfeldt and Papanikolaou (2013) divided by Total Assets.

Measure	Mean	Std. Dev.	p10	p50	p90	Obs.
Generative AI Exposure	0.354	0.078	0.268	0.353	0.442	2,518
Log Size	1.876	2.381	-1.091	2.063	4.636	2,517
Tobin’s Q	3.667	10.081	1.354	2.176	5.832	2,380
ROA	-0.011	0.891	-0.181	0.093	0.216	2,513
Labor Intensity	0.761	1.761	-2.157	1.126	2.512	2,387
Org. Capital Ratio	1.190	4.416	0.137	0.712	2.179	1,571
Tangibility	0.301	0.266	0.036	0.198	0.758	2,515

Table II: Major U.S. Firms with the Highest and Lowest Exposure to GPT. This table shows the 15 large U.S. publicly traded firms with the highest employee exposure to ChatGPT in Panel A and the 15 firms with the lowest exposure in Panel B. We select the large U.S. publicly traded firms as the top 100 firms with the largest market capitalization as of November 1, 2022, which also have headquarters in the U.S. *Generative AI exposure* is the firm’s labor exposure to ChatGPT-like technologies defined in Section I. *MktCap* is the firm’s market capitalization as of November 1, 2022, in \$B. *Sector* is defined at the NAICS 2-digit level.

Panel A: Top 15 Large U.S. Companies with Highest Exposure to ChatGPT			
Company Name	Generative AI exposure	MktCap	Sector
Int. Business Machines Corp	0.488	125	Information
Intuit Inc.	0.480	111	Information
QUALCOMM Inc.	0.479	132	Manufacturing
Fiserv Inc.	0.475	66	Information
NVIDIA Corporation	0.468	337	Manufacturing
S&P Global Inc	0.452	103	Admin. & Support Services
Broadcom Inc	0.449	195	Manufacturing
Verizon Communications Inc	0.444	157	Information
Microsoft Corp	0.442	1,700	Information
3M Co	0.442	69	Manufacturing
Advanced Micro Devices Inc	0.441	96	Manufacturing
ServiceNow Inc	0.434	85	Information
Adobe Inc	0.427	147	Information
PayPal Holdings Inc	0.418	96	Information
Thermo Fisher Scientific Inc	0.411	203	Manufacturing
Panel B: Bottom 15 Large U.S. Companies with Lowest Exposure to ChatGPT			
Company Name	Generative AI exposure	MktCap	Sector
Starbucks Corp	0.119	100	Accommodation & Food Svcs
McDonald’s Corp	0.194	201	Accommodation & Food Svcs
Dollar General Corporation	0.212	57	Retail Trade
Target Corp	0.235	76	Retail Trade
Walmart Inc	0.235	385	Retail Trade
Lowe’s Cos Inc	0.238	120	Retail Trade
TJX Companies Inc	0.243	83	Retail Trade
Costco Wholesale Corp	0.252	221	Retail Trade
Union Pacific Corp	0.253	121	Transportation & Warehousing
CSX Corp	0.256	61	Transportation & Warehousing
United Parcel Service Inc	0.256	123	Transportation & Warehousing
Home Depot Inc	0.261	303	Retail Trade
Tesla Inc	0.283	719	Manufacturing
Northrop Grumman Corp	0.291	83	Manufacturing
Mondelez International Inc	0.292	85	Manufacturing

Table III: Firm Generative AI exposure and Firm Characteristics This table regresses our firms' Generative AI exposure measure on firm characteristics using the cross-section of U.S. publicly traded firms in 2022. See Table I for variable definitions. Panel B controls for fixed effects at the NAICS 3-digit level. All variables are winsorized at the top and bottom 1%. Standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Across All Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
Log Size	-2.653** (1.199)					
Tobin's Q		3.076*** (0.798)				
ROA			-21.516* (11.100)			
Labor Intensity				7.892*** (2.325)		
Org. Capital Ratio					9.139*** (2.506)	
Tangibility						-89.931*** (20.961)
Observations	2517	2380	2513	2387	1571	2515
Adjusted R^2	0.006	0.013	0.006	0.038	0.022	0.107
Panel B: Within-Industry						
	(1)	(2)	(3)	(4)	(5)	(6)
Log Size	-0.730 (1.021)					
Tobin's Q		0.524 (0.661)				
ROA			-7.303 (10.112)			
Labor Intensity				5.593*** (1.559)		
Org. Capital Ratio					1.111 (1.870)	
Tangibility						-61.794** (25.082)
Observations	2517	2380	2513	2387	1571	2515
Adjusted R^2	0.280	0.292	0.279	0.313	0.312	0.298

Table IV: Realized returns of portfolios sorted on Generative AI exposure after ChatGPT release: quintile portfolios. This table reports daily excess stock returns of value-weighted portfolios of firms sorted on Generative AI exposure. *AMH* is the "Artificial Minus Human" zero net investment portfolio long high exposure (*H*) stocks and short low exposure (*L*) stocks. Quintile thresholds that define value-weighted portfolios are solely based on the sample of stocks listed on NYSE as of the sorting date. All quintile portfolios are formed based on equalweighted sorts on November 14, 2022, and weights are adjusted based on daily returns to mimic passive buy-and-hold exposure. Industry-neutral portfolios are computed by first forming within-industry value-weighted quintile portfolios, and then averaging portfolio returns for the same quintiles across industries. Returns for within-industry quintiles are value-weighted, while across-industry averages are industry market-cap. weighted. The data set consists of daily stock returns from Yahoo Finance for Nov. 15, 2022 - March 31, 2023. The Fama-French factors, including the market factor and risk free returns are obtained from Ken French's website. The table shows alphas estimated from regressions of the form

$$r_{it}^{pf} - r_t^f = \alpha_i^{\text{release}} \mathbb{1}[\text{ChatGPT release period}]_t + \alpha_i^{\text{not release}} \mathbb{1}[\text{Not ChatGPT release period}]_t + \beta_i(Mkt_t - r_t^f) + \varepsilon_{it},$$

where the intercept is either for the full sample, or is allowed to vary with whether the day is in the ChatGPT release period consisting of Nov 30, 2022 - Dec. 14, 2022. Panel A reports excess returns net of the risk free rate and does not include any additional controls. Panel B controls for variation in the market factor. Panel C controls for returns on the Fama French 5-factors when computing the period alphas. T-statistics in parentheses are computed using Newey-West standard errors with five lags.

Sample	Portfolios					
	Q1	Q2	Q3	Q4	Q5	AMH
<i>A: Excess returns (%)</i>						
Not ChatGPT release period	0.071 (0.59)	0.030 (0.26)	0.038 (0.34)	0.045 (0.38)	0.096 (0.77)	0.008 (0.14)
ChatGPT release period	-0.169 (-0.65)	0.020 (0.06)	0.141 (0.43)	0.035 (0.12)	0.281 (0.76)	0.434 (3.54)
<i>B: Market-factor-adjusted alpha (%)</i>						
Not ChatGPT release period	0.047 (1.09)	0.003 (0.09)	0.011 (0.30)	0.018 (0.44)	0.065 (1.90)	0.002 (0.04)
ChatGPT release period	-0.230 (-5.49)	-0.045 (-0.44)	0.075 (1.01)	-0.031 (-0.88)	0.207 (4.86)	0.420 (5.65)
<i>C: FF 5-factor-adjusted alpha (%)</i>						
Not ChatGPT release period	0.067 (1.57)	0.019 (0.56)	-0.023 (-0.81)	0.033 (1.13)	0.052 (1.94)	-0.031 (-0.55)
ChatGPT release period	-0.167 (-2.38)	0.014 (0.16)	-0.020 (-0.57)	0.026 (0.66)	0.157 (3.53)	0.309 (3.56)
<i>D: FF 5-factor-adjusted alpha ex. tech sector (%)</i>						
Not ChatGPT release period	0.068 (1.56)	0.013 (0.35)	-0.023 (-0.68)	-0.019 (-0.74)	0.073 (2.35)	-0.011 (-0.20)
ChatGPT release period	-0.171 (-2.40)	0.022 (0.22)	0.011 (0.32)	0.048 (1.01)	0.171 (1.94)	0.327 (3.51)

Table V: Realized returns of portfolios sorted on Generative AI exposure after ChatGPT release. This table reports daily excess stock returns of value-weighted portfolios of firms sorted on Generative AI exposure. *AMH* is the "Artificial Minus Human" zero net investment portfolio long high exposure (*H*) stocks and short low exposure (*L*) stocks. Tercile thresholds that define value-weighted portfolios are solely based on the sample of stocks listed on NYSE as of the sorting date. All tercile portfolios are formed based on equalweighted sorts on November 14, 2022, and weights are adjusted based on daily returns to mimic passive buy-and-hold exposure. Industry-neutral portfolios are computed by first forming within-industry value-weighted tercile portfolios, and then averaging portfolio returns for the same terciles across industries. Returns for within-industry terciles are value-weighted, while across-industry averages are industry market-cap. weighted. The data set consists of daily stock returns from Yahoo Finance for Nov. 15, 2022 - March 31, 2023. The Fama-French factors, including the market factor and risk free returns are obtained from Ken French's website. The table shows alphas estimated from regressions of the form

$$r_{it}^p - r_t^f = \alpha_i^{\text{release}} \mathbb{I}[\text{ChatGPT release period}]_t + \alpha_i^{\text{not release}} \mathbb{I}[\text{Not ChatGPT release period}]_t + \sum_{fac \in FF5} \beta_i^{fac} r_t^{fac} + \varepsilon_{it},$$

where the intercept is either for the full sample, or is allowed to vary with whether the day is in the ChatGPT release period consisting of Nov 30, 2022 - Dec. 14, 2022. Panels A and B form industry-neutral portfolios by sorting stocks within NAICS 3-digit industries. Panel C and D forms industry-neutral portfolios using the 2021 data version of Hoberg and Phillips (2016) FIC-50 industry definitions, formed by clustering firms based on the similarity of product descriptions in their annual reports. All panels report industry-neutral factor adjusted alphas in % and only keep industries that have at least 10 firms in the sample. Panels A and C include the market factor as a control variable, while panels B and D control for returns on the Fama French 5-factors when computing the period alphas. T-statistics in parentheses are computed using Newey-West standard errors with five lags.

Sample	Portfolios			
	Q1	Q2	Q3	AMH
<i>A1: Market-factor-adjusted alpha (%)</i>				
Not ChatGPT release period	0.032 (1.13)	0.028 (1.15)	0.036 (1.72)	-0.013 (-0.32)
ChatGPT release period	-0.170 (-3.19)	0.069 (1.41)	0.123 (2.83)	0.277 (3.71)
<i>A2: NAICS3 ind.-neutral market-factor-adjusted alpha (%)</i>				
Not ChatGPT release period	0.035 (1.36)	0.020 (0.59)	0.035 (2.07)	-0.017 (-0.58)
ChatGPT release period	-0.158 (-3.97)	0.035 (0.62)	0.144 (9.96)	0.286 (5.77)
<i>A3: FIC50 ind.-neutral market-factor-adjusted alpha (%)</i>				
Not ChatGPT release period	0.044 (0.91)	-0.015 (-0.79)	0.021 (1.00)	-0.039 (-0.79)
ChatGPT release period	-0.187 (-3.17)	0.053 (1.02)	0.128 (2.28)	0.299 (2.88)
<i>B1: FF 5-factor-adjusted alpha (%)</i>				
Not ChatGPT release period	0.051 (2.07)	0.008 (0.48)	0.034 (1.69)	-0.033 (-0.86)
ChatGPT release period	-0.102 (-2.58)	0.005 (0.21)	0.123 (2.47)	0.210 (2.51)
<i>B2: NAICS3 ind.-neutral FF 5-factor-adjusted alpha (%)</i>				
Not ChatGPT release period	0.052 (2.50)	0.041 (1.82)	0.032 (1.88)	-0.036 (-1.32)
ChatGPT release period	-0.113 (-2.95)	0.077 (1.34)	0.128 (6.22)	0.226 (4.61)
<i>B3: FIC50 ind.-neutral FF 5-factor-adjusted alpha (%)</i>				
Not ChatGPT release period	0.075 (2.00)	-0.007 (-0.56)	0.022 (1.08)	-0.069 (-1.54)
ChatGPT release period	-0.119 (-2.30)	0.100 (1.64)	0.119 (2.39)	0.222 (2.54)

Table VI: Heterogeneity in firm-level effects of Generative AI exposure on returns: The data set consists of daily stock returns from Yahoo Finance for Nov. 15, 2022 - March 31, 2023. The market factor and risk free returns are obtained from Ken French's website. The table shows selected coefficients estimated from regressions of the form

$$r_{it} - r_t^f = \beta^{\text{release}} [\% \text{High exposure}]_i \times \mathbb{1} [\text{ChatGPT release}]_t + \beta^{\text{interact}} [\% \text{High exposure}]_i \times \mathbb{1} [\text{ChatGPT release}]_t \times [\text{Firm Char.}]_i \\ + \beta^{\text{char}} \times \mathbb{1} [\text{ChatGPT release}]_t \times [\text{Firm Char.}]_i + \alpha^{\text{release}} \\ \gamma^{\text{notrelease}} [\% \text{High exposure}]_i \times \mathbb{1} [\text{Not ChatGPT release}]_t + \gamma^{\text{interact}} [\% \text{High exposure}]_i \times \mathbb{1} [\text{Not ChatGPT release}]_t \times [\text{Firm Char.}]_i \\ + \gamma^{\text{char}} \times \mathbb{1} [\text{Not ChatGPT release}]_t \times [\text{Firm Char.}]_i + \alpha^{\text{not release}} + \beta^{\text{mkt}} (Mkt_t - r_t^f) + \varepsilon_{it},$$

where the intercept for the panel is allowed to vary with whether the day is in the ChatGPT release period consisting of Nov 30, 2022 - Dec. 14, 2022. High exposure occupations are defined as the top decile of occupations based on their task Generative AI exposure. All regressions allow for average returns to vary across the release and non-release periods and also control for exposure to the market factor, and the interaction of the firm characteristic of interest with the release and non-release period indicators. Column (1) shows the baseline effect of the high exposure occupation employment share at a firm on daily returns during the post-ChatGPT two week release period. Columns (2)-(4) shows how this exposure effect varies with the firm's hiring for jobs with AI skills in 2018-2021, showing the heterogeneity, respectively, with regard to any AI skill hiring over that period, the share of all listed positions that mentioned AI skills, and the log of total advertised jobs requiring AI skills. Columns (5) and (6) show the interactions with the share of job titles of the firm's job postings 2018-2021 that suggest either a role focused on AI or on advanced computing topics more generally. Column (7) interacts with the share of the share of employees on LinkedIn of the company that work in computer-related occupations. Column (8) allows for different effects in NAICS sectors 51 and 54 relative to the rest of the sample. T-statistics in parentheses are computed using Newey-West standard errors with five lags.

Dep. var.:	Daily Firm-level Excess Returns (ppt)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{1} [\text{Release Period}]_t \times \text{High GenAI Exposure}_i$	0.742*** (3.575)	0.690*** (3.048)	0.741*** (3.570)	0.623*** (2.994)	0.747*** (3.599)	0.715*** (3.376)	0.799*** (3.875)	0.681*** (3.152)	0.591** (2.486)
$\mathbb{1} [\text{Release Period}]_t \times \text{Tech Sector}_i$		0.063 (0.593)							-0.039 (-0.454)
$\mathbb{1} [\text{Release Period}]_t \times \text{Log Size}_i$			0.001 (0.097)						0.041** (2.126)
$\mathbb{1} [\text{Release Period}]_t \times \text{Tobin's } Q_i$				0.051*** (5.373)					0.045*** (4.331)
$\mathbb{1} [\text{Release Period}]_t \times \text{ROA}_i$					0.049 (0.184)				0.165 (0.670)
$\mathbb{1} [\text{Release Period}]_t \times \text{Labor Intensity}_i$						0.032* (1.772)			0.095*** (2.855)
$\mathbb{1} [\text{Release Period}]_t \times \text{Org. Capital Ratio}_i$							-0.026 (-0.718)		-0.041 (-1.037)
$\mathbb{1} [\text{Release Period}]_t \times \text{Tangibility}_i$								-0.151 (-1.494)	-0.025 (-0.137)
R-squared	0.07	0.07	0.07	0.07	0.07	0.07	0.14	0.07	0.14
Observations	195210	195210	195210	195210	194740	192954	101447	194364	101165
NAICS3 FE									
Day FE	X	X	X	X	X	X	X	X	X
Firm Characteristics	X	X	X	X	X	X	X	X	X

Controls & fixed effects

Table VII: Firm hiring effects of Generative AI exposure: The table shows selected coefficients estimated from regressions of the form

$$\text{Hiring}_i = \alpha_i + \alpha_t + \chi \mathbb{1}[\text{Post-ChatGPT}]_t \times [\text{Gen. AI Exposure}]_i + \varepsilon_{it},$$

in a panel of firm-level monthly job postings for 2010-2023 constructed from Lightcast data. High exposure occupations are defined as the top decile of occupations based on their task Generative AI exposure, and their share of employment is calculated from 2022 employment in LinkedIn data obtained from Revelio Labs. The post-chatGPT period is defined as all months after November 2022. The columns show, in order, the differential effect of Generative AI exposure among employment in 2022 at a firm on the post-ChatGPT change in the share (panel A) or level (panel B) of job postings for workers whose job title suggests a role focused on artificial intelligence (Column 1); a job title that suggests a role focused on advanced computing topics (Column 2); jobs requiring AI skills (Column 3); jobs in high Generative AI exposure occupations (Column 4); non-college jobs (Column 5); jobs requiring at least a college degree (Column 6); jobs requiring an advanced degree (Column 7); jobs in management occupations (Column 8); and total hiring (Column 9). Panel C and D repeat the same analysis but control for differential trends post-ChatGPT that vary with a firm's stock of computer-related occupation employees in 2022. T-statistics in parentheses are computed with standard errors clustered at both the year-month level and the firm level.

Job category:	All (1)	High GenAI Exposure (2)	AI Skills (3)
<i>A: Number of firm's job postings in the category</i>			
$\mathbb{1}[\text{Post-ChatGPT}]_t \times \text{GenAI Exposure}_i$	-1409.034*** (-4.664)	-158.298*** (-3.446)	4.328 (0.775)
<i>B: Percentage of firm's job postings in the category</i>			
$\mathbb{1}[\text{Post-ChatGPT}]_t \times \text{GenAI Exposure}_i$		-0.079** (-2.282)	0.062*** (6.236)
Observations	338,489	338,489	338,489
Year-Month FE	X	X	X
Firm FE	X	X	X

Appendix A. Appendix: Methodology Notes

Generative AI exposure portfolio construction.

Portfolios for the main realized return analysis are formed from quintiles of stocks that have Yahoo Finance data for Nov. 15, 2022 - March 31, 2023. Quintile thresholds that define value-weighted portfolios within industries or for all stocks are solely based on the sample of stocks listed on NYSE as of the sorting date. All portfolios are formed based on equal weighted sorts on November 14, 2022, and weights for computing portfolio returns are adjusted based on daily returns to mimic passive buy-and-hold exposure. Industry-neutral portfolios are computed by first forming within-industry value-weighted quintile portfolios, and then averaging portfolio returns for the same quintiles across industries. Returns for within-industry quintiles and for all global (not industry-neutral) portfolio sorts are value-weighted, while across-industry averages are industry market-cap. weighted. *AMH* is the "Artificial Minus Human" (also referred to as H-L) is the zero net investment portfolio long highest exposure quintile (*H*) stocks and short lowest exposure quintile (*L*) stocks.

GPT prompt for exposure scoring

The following prompt structure was based on the rubric language by Eloundou et al. (2023), as well as insights by Willison (2023) and Underwood (2023) about how to best structure API calls for GPT classification. Here are the instruction prompts submitted before asking GPT 3.5 Turbo to classify each task statement (using the version as of March 28th, 2023). Note that the order in which the two user-assistant interactions are provided to the API is randomized for each task, and the GPT temperature is set to 0:

systemprompt = "Consider the most powerful OpenAI large language model (LLM). This model can complete many tasks that can be formulated as having text input and text output where the context for the input can be captured in 2000 words. The model also cannot draw up-to-date facts (those from <1 year ago) unless they are captured in the input. Assume you are a worker with an average level of expertise in your role trying to complete the given task. You have access to the LLM as well as any other existing software or computer hardware tools mentioned in the task. You also have access to any commonly available technical tools accessible via a laptop (e.g. a microphone, speakers, etc.). You do not have access to any other physical tools or materials. You are a helpful research assistant who wants to label the given tasks according to the rubric below. Equivalent quality means someone reviewing the work would not be able to tell whether a human completed it on their

own or with assistance from the LLM. If you aren't sure how to judge the amount of time a task takes, consider whether the tools described exposed the majority of subtasks associated with the task.

Exposure rubric:

E1 - Direct exposure: Label tasks E1 if direct access to the LLM through an interface like ChatGPT or the OpenAI playground alone can reduce the time it takes to complete the task with equivalent quality by at least half. This includes tasks that can be reduced to: - Writing and transforming text and code according to complex instructions, - Providing edits to existing text or code following specifications, - Writing code that can help perform a task that used to be done by hand, - Translating text between languages, - Summarizing medium-length documents, - Providing feedback on documents, - Answering questions about a document, - Generating questions a user might want to ask about a document, - Writing questions for an interview or assessment, - Writing and responding to emails, including ones that involve refuting information or engaging in a negotiation (but only if the negotiation is via written correspondence), - Maintain records of written data, - Prepare training materials based on general knowledge, or - Inform anyone of any information via any written or spoken medium.

E2 - Exposure by LLM-powered applications: Label tasks E2 if having access to the LLM alone may not reduce the time it takes to complete the task by at least half, but it is easy to imagine additional software that could be developed on top of the LLM that would reduce the time it takes to complete the task by half. This software may include capabilities such as: - Summarizing documents longer than 2000 words and answering questions about those documents, - Retrieving up-to-date facts from the Internet and using those facts in combination with the LLM capabilities, - Searching over an organization's existing knowledge, data, or documents and retrieving information, - Retrieving highly specialized domain knowledge, - Make recommendations given data or written input, - Analyze written information to inform decisions, - Prepare training materials based on highly specialized knowledge, - Provide counsel on issues, and - Maintain complex databases.

E3 - Exposure given image capabilities: Suppose you had access to both the LLM and a system that could view, caption, and create images as well as any systems powered by the LLM (those in E2 above). This system cannot take video as an input and it cannot produce video as an output. This system cannot accurately retrieve very detailed information from image inputs, such as measurements of dimensions within an image. Label tasks as E3 if there is a significant reduction in the time it takes to complete the task given access to a LLM and these image capabilities: - Reading text from PDFs, - Scanning images, or - Creating or editing digital images according to instructions. The images can be realistic but they

should not be detailed. The model can identify objects in the image but not relationships between those options

E0 - No exposure: Label tasks E0 if none of the above clearly decrease the time it takes for an experienced worker to complete the task with high quality by at least half. Some examples: - If a task requires a high degree of human interaction (for example, in-person demonstrations) then it should be classified as E0. - If a task requires precise measurements then it should be classified as E0. - If a task requires reviewing visuals in detail then it should be classified as E0. - If a task requires any use of a hand or walking then it should be classified as E0. - Tools built on top of the LLM cannot make any decisions that might impact human livelihood (e.g. hiring, grading, etc.). If any part of the task involves collecting inputs to make a final decision (as opposed to analyzing data to inform a decision or make a recommendation) then it should be classified as E0. The LLM can make recommendations. - Even if tools built on top of the LLM can do a task, if using those tools would not save an experienced worker significant time completing the task, then it should be classified as E0. - The LLM and systems built on top of it cannot do anything that legally requires a human to perform the task. - If there is existing technology not powered by an LLM that is commonly used and can complete the task then you should mark the task E0 if using an LLM or LLM-powered tool will not further reduce the time to complete the task. When in doubt, you should default to E0."

user_prompts = ["", "", "", ""] user_prompts[0] = "Read the following occupation title and one of the tasks that belong to that occupation. Then do three things. 1: Reason step by step to decide which of the labels (E0/E1/E2/E3) from the exposure rubric you were given applies to the task's exposure to LLM. Report. Give an explanation for which label applies and report the label that you think fits best. Do not say zero or N/A.

2: Report only the label that you determined for the task, which should match the label in step 1. Do not reply N/A.

3: Given the amount of speculation required in step 1, describe your certainty about the estimate—either high, moderate, or low.

The task to label follows:

Occupation: Inspectors, Testers, Sorters, Samplers, and Weighers. Task: Adjust, clean, or repair products or processing equipment to correct defects found during inspections."

assistant_prompts = ["", "", "", ""] assistant_prompts[0] = "1: Label (E0/E1/E2/E3): E0. Explanation: The model does not have access to any kind of physicality, and more than half of the task (adjusting, cleaning and repairing equipment) described requires hands or other embodiment.

2: E0.

3: High confidence.”

user_prompts[1] = "Read the following occupation title and one of the tasks that belong to that occupation. Then do three things. 1: Reason step by step to decide which of the labels (E0/E1/E2/E3) from the exposure rubric you were given applies to the task's exposure to LLM. Report. Give an explanation for which label applies and report the label that you think fits best. Do not say zero or N/A.

2: Report only the label that you determined for the task, which should match the label in step 1. Do not reply N/A.

3: Given the amount of speculation required in step 1, describe your certainty about the estimate—either high, moderate, or low.

The task to label follows:

Occupation: Computer and Information Research Scientists. Task: Apply theoretical expertise and innovation to create or apply new technology, such as adapting principles for applying computers to new uses.”

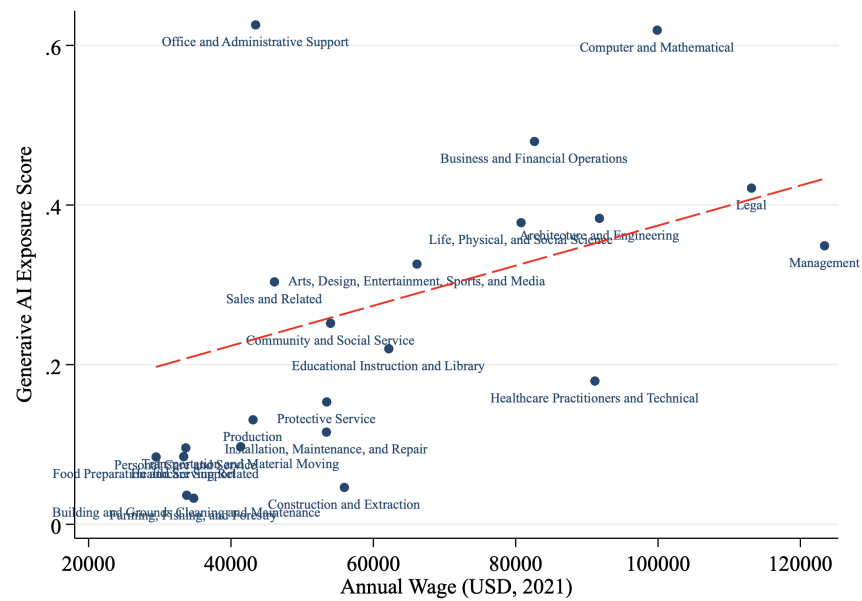
assistant_prompts[1] = "1: Label (E0/E1/E2/E3): E1. Explanation: The model can learn theoretical expertise during training as part of its general knowledge base, and the principles to adapt can be captured in the text input to the model.

2: E1.

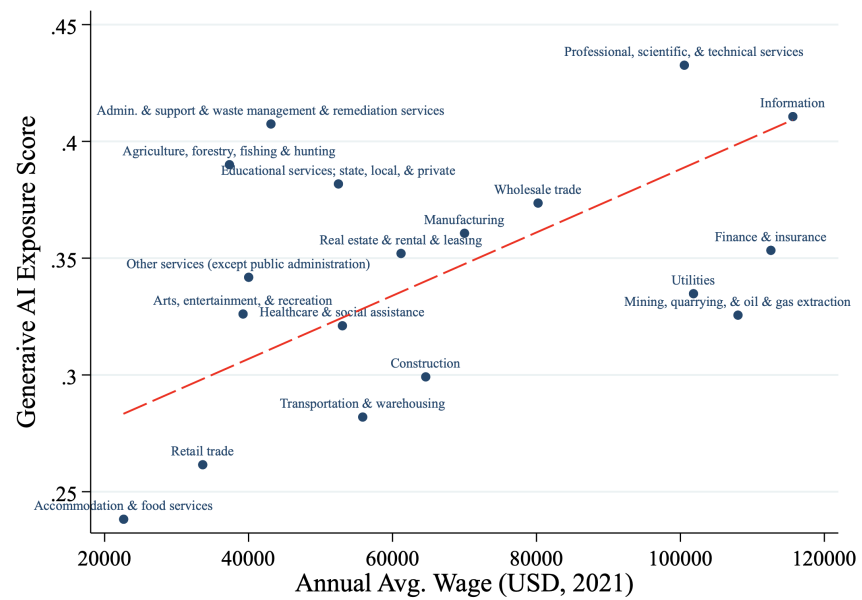
3: Medium confidence.”

Appendix B. Appendix Figures

Figure B1: Generative AI exposure and wages by major occupation group and industry sectors.



(A) Major occupation groups

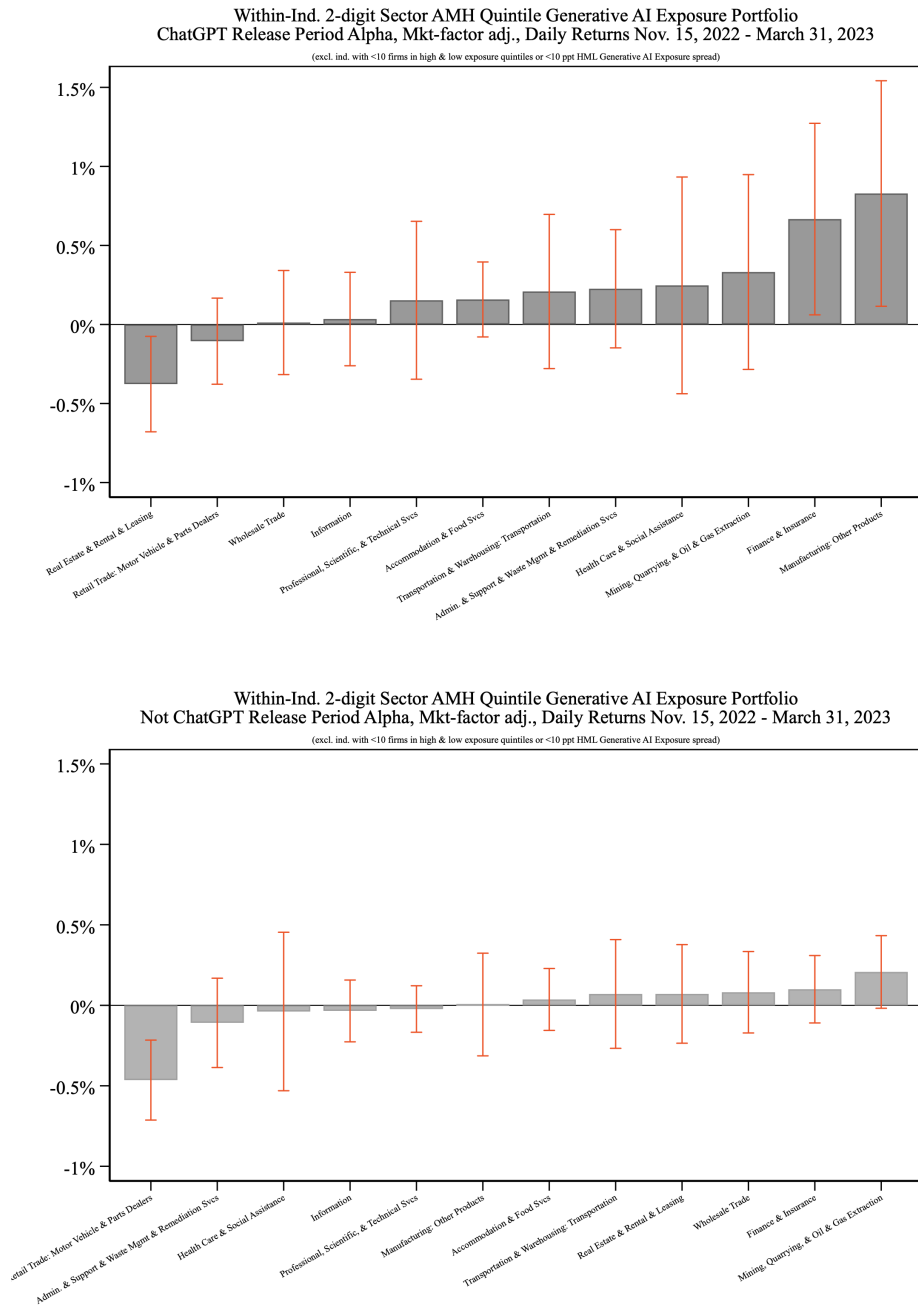


(B) NAICS 2-digit industry sectors

Figure B2: Within-Sector *AMH* Generative AI exposure Portfolio Realized Returns: ChatGPT Release Period. The graph shows the average daily return alpha for the ChatGPT release period for *AMH* Generative AI exposure portfolios within each industry, at the 2-digit NAICS sector level. Each *AMH* portfolio is formed by taking the value-weighted highest and lowest quintiles of Generative AI exposure within each industry (based on NYSE stock cutoffs) and forming zero net investment *AMH* portfolio returns as the equal-weighted difference in the daily realized returns between these portfolios, and then subtracting the daily risk-free return. The industries shown omit any sectors with fewer than 10 firms combined in the highest and lowest quintiles in the sample, as well as sectors with less than a 10 ppt Generative AI exposure spread at the sector level between the high and low quintile. The data set consists of daily stock returns from Yahoo Finance for Nov. 15, 2022 - March 31, 2023. The graphs show market-factor adjusted alphas estimated from regressions of the form

$$r_{it}^{pf} - r_t^f = \alpha_i^{\text{release}} \mathbb{1}[\text{ChatGPT release period}]_t + \alpha_i^{\text{not release}} \mathbb{1}[\text{Not ChatGPT release period}]_t + \beta_i(Mkt_t - r_t^f) + \varepsilon_{it},$$

where the intercept is allowed to vary with whether the day is in the release period defined by Nov. 30, 2022 - Dec. 14, 2022, or is one of the other trading days in the sample. The returns are shown in units of average daily excess realized returns (controlling for the market factor). Red error bars indicate 95% confidence intervals computed using Newey-West standard errors with five lags.



Appendix C. Appendix Tables

Occupation	Task ID	Task	GPT Score	GPT Explanation
Secretaries and Administrative Assistants, Except Legal, Medical, and Executive Nuclear Technicians	20283	Operate office equipment, such as fax machines, copiers, or phone systems and arrange for repairs when equipment malfunctions.	0	The task requires physical interaction with office equipment, which cannot be done by the LLM.
	22315	Monitor instruments, gauges, or recording devices under direction of nuclear experimenters.	0	The task requires monitoring physical instruments and gauges, which cannot be done by the LLM.
	4180	Administer emergency first aid, such as performing emergency resuscitation or other life saving procedures.	0	The task requires hands-on physical intervention and cannot be completed through text input/output alone.
Penetration Testers	21754	Document penetration test findings.	1	The model can be trained on penetration testing and can generate text output based on the input.
Gambling Dealers	4453	Open and close cash floats and game tables.	0	The task requires physical interaction with cash and game tables, and the LLM cannot perform any physical actions.
Agricultural Engineers	5337	Meet with clients, such as district or regional councils, farmers, and developers, to discuss their needs.	0	The task requires human interaction and communication skills, which cannot be replaced by the LLM.
Farm Equipment Mechanics and Service Technicians	13750	Maintain, repair, and overhaul farm machinery and vehicles, such as tractors, harvesters, and irrigation systems.	0	The task requires physical maintenance and repair of machinery and vehicles, which cannot be done by the LLM.
Adult Basic Education, Adult Secondary Education, and English as a Second Language Instructors	6846	Meet with other professionals to discuss individual students' needs and progress.	1	The model can assist in writing and responding to emails, including those that involve discussing student progress with other professionals.
Payroll and Timekeeping Clerks	2526	Distribute and collect timecards each pay period.	0	The task does not involve writing or transforming text, nor does it require any complex decision-making or analysis that the LLM could assist with.
Environmental Engineering Technologists and Technicians	3647	Obtain product information, identify vendors or suppliers, or order materials or equipment to maintain inventory.	2	The model can help identify vendors or suppliers by searching the internet and retrieving information. It can also help order materials or equipment by generating text that can be sent to suppliers.

Table C1: Examples of GPT scores assigned to task statements and GPT-provided explanations.

Table C2: Exposure score variation across GPT scoring runs

Score comparison	Agreement %		
	Current Exposure	Expected exposure	Broad exposure
GPT #1 vs. GPT #2	95	90	90
GPT #1 vs. GPT #3	93	88	88
GPT #2 vs. GPT #3	96	88	88

SOC Code	Occupation Title	Exposure Score
41-9041	Telemarketers	.96
43-9081	Proofreaders and copy markers	.95
43-3031	Bookkeeping, accounting, and auditing clerks	.87
15-2021	Mathematicians	.86
15-1251	Computer programmers	.85
43-9022	Word processors and typists	.85
43-3011	Bill and account collectors	.83
27-3091	Interpreters and translators	.82
43-9111	Statistical assistants	.82
15-1254	Web developers	.81
43-6011	Executive secretaries and executive administrative assistants	.77
43-3051	Payroll and timekeeping clerks	.77
43-6014	Secretaries and administrative assistants, except legal, medical, and executive	.77
43-5061	Production, planning, and expediting clerks	.76
15-1212	Information security analysts	.75
43-6013	Medical secretaries and administrative assistants	.75
27-3043	Writers and authors	.75
43-4021	Correspondence clerks	.74
43-9061	Office clerks, general	.74
41-3091	Sales representatives of services, except advertising, insurance, financial services, and travel	.73
:	:	:
39-5093	Shampooers	0
51-6041	Shoe and leather workers and repairers	0
51-6042	Shoe machine operators and tenders	0
51-3023	Slaughterers and meat packers	0
47-2022	Stonemasons	0
47-2221	Structural iron and steel workers	0
51-2041	Structural metal fabricators and fitters	0
29-9093	Surgical assistants	0
51-6052	Tailors, dressmakers, and custom sewers	0
47-2082	Tapers	0
49-9052	Telecommunications line installers and repairers	0
47-2053	Terrazzo workers and finishers	0
51-6064	Textile winding, twisting, and drawing out machine setters, operators, and tenders	0
47-2044	Tile and stone setters	0
51-9197	Tire builders	0
49-3093	Tire repairers and changers	0
51-4194	Tool grinders, filers, and sharpeners	0
39-3031	Ushers, lobby attendants, and ticket takers	0
49-9064	Watch and clock repairers	0
53-7073	Wellhead pumpers	0

Table C3: Highest and lowest Generative AI exposure score occupations

NAICS Code	Industry Title	Exposure Score
54	Professional, Scientific, and Technical Svcs	.43
51	Information	.41
56	Admin. and Support and Waste Mgmt and Remed. Svcs	.4
52	Finance and Insurance	.4
42	Wholesale Trade	.38
61	Educational Svcs	.37
11	Agriculture, Forestry, Fishing and Hunting	.37
33	Manufacturing: Other Products	.36
32	Manufacturing: Textile, Apparel, and Leather	.35
71	Arts, Entertainment, and Recreation	.33
22	Utilities	.33
62	Health Care and Social Assistance	.32
31	Manufacturing: Food, Beverage, and Tobacco	.31
81	Other Svcs (except Public Administration)	.31
21	Mining, Quarrying, and Oil and Gas Extraction	.31
49	Transp. and Warehousing: Warehousing and Storage	.3
23	Construction	.3
53	Real Estate and Rental and Leasing	.27
48	Transp. and Warehousing: Transportation	.27
44	Retail Trade: Motor Vehicle and Parts Dealers	.27
45	Retail Trade: Other Merchandise	.27
72	Accommodation and Food Svcs	.21

Table C4: Generative AI exposure scores by industry

Table C5: Generative AI exposure for the Largest 100 U.S. Firms This table lists

the Generative AI exposure scores for the largest 100 publicly-traded firms with headquarters in the U.S., where size is measured as the market capitalization as of November 1, 2022. *Generative AI exposure* is the firm’s labor exposure defined in Section I. *MktCap* is the firm’s market capitalization as of November 1, 2022, in \$. *Sector* is defined at the NAICS 2-digit level.

Company Name	Gen. AI exposure	MktCap	Sector
International Business Machines Corp	0.488	125	Information
Intuit Inc.	0.480	111	Information
QUALCOMM Inc.	0.479	132	Manufacturing
Fiserv Inc.	0.475	66	Information
NVIDIA Corporation	0.468	337	Manufacturing
S&P Global Inc	0.452	103	Administrative and Support and Waste Management and Remediation Services
Broadcom Inc	0.449	195	Manufacturing
Verizon Communications Inc	0.444	157	Information
Microsoft Corp	0.442	1,701	Information
3M Co	0.442	69	Manufacturing
Advanced Micro Devices Inc	0.441	96	Manufacturing
ServiceNow Inc	0.434	85	Information
Adobe Inc	0.427	147	Information
PayPal Holdings Inc	0.418	96	Information
Thermo Fisher Scientific Inc	0.411	203	Manufacturing
Intuitive Surgical Inc	0.404	87	Manufacturing
Automatic Data Processing Inc	0.398	101	Information
Concast Corp	0.396	136	Information
Vertex Pharmaceuticals Inc	0.395	81	Manufacturing
Analog Devices Inc	0.392	74	Manufacturing
AbbVie Inc	0.391	260	Manufacturing
Regeneron Pharmaceuticals Inc	0.390	81	Manufacturing
Gilead Sciences Inc	0.388	99	Manufacturing
Micron Technology Inc.	0.388	60	Manufacturing
Intel Corp	0.386	117	Manufacturing
Bristol-Myers Squibb Co	0.385	165	Manufacturing
Illinois Tool Works Inc.	0.382	66	Manufacturing
Netflix Inc	0.381	128	Real Estate and Rental and Leasing
Meta Platforms Inc	0.381	217	Information
Lam Research Corp	0.380	56	Manufacturing
SALESFORCE INC	0.379	160	Information
General Dynamics Corp	0.378	69	Manufacturing
Abbott Laboratories	0.376	174	Manufacturing
AT&T Inc	0.375	131	Information
Applied Materials Inc	0.374	77	Manufacturing
Booking Holdings Inc	0.373	75	Information
General Electric Co	0.373	85	Wholesale Trade
Merck & Co Inc	0.372	253	Manufacturing
T-Mobile US Inc	0.371	189	Information
Johnson & Johnson	0.371	453	Manufacturing
Honeywell International Inc	0.368	137	Manufacturing
Alphabet Inc	0.366	546	Information
Amgen Inc	0.365	146	Manufacturing
Ellie Lilly and Co	0.364	335	Manufacturing
Apple Inc	0.364	2,397	Manufacturing
Philip Morris International Inc	0.364	142	Manufacturing
DEERE & COMPANY	0.364	117	Manufacturing
Texas Instruments Inc	0.363	148	Manufacturing
Caterpillar Inc	0.358	115	Manufacturing
CVS Health Corp	0.356	124	Health Care and Social Assistance
Cisco Systems Inc	0.355	187	Manufacturing
Zetis Inc	0.355	71	Manufacturing
Pfizer Inc	0.352	269	Manufacturing
Southern Co (The)	0.351	71	Utilities
Danaher Corp	0.350	186	Manufacturing
Procter & Gamble Co (The)	0.342	320	Manufacturing
Raytheon Technologies Corp	0.339	140	Manufacturing
Colgate-Palmolive Co	0.337	62	Manufacturing
Becton Dickinson and Co	0.331	67	Manufacturing
Dominion Energy Inc	0.330	58	Utilities
NextEra Energy Inc	0.329	154	Utilities
Walt Disney Co (The)	0.328	193	Information
Altria Group Inc	0.327	83	Manufacturing
Air Products and Chemicals Inc.	0.326	56	Manufacturing
Waste Management Inc.	0.325	64	Administrative and Support and Waste Management and Remediation Services
Duke Energy Corp	0.322	72	Utilities
EOG Resources Inc.	0.322	80	Mining, Quarrying, and Oil and Gas Extraction
Exxon Mobil Corp	0.320	466	Manufacturing
Amazon.com Inc	0.317	987	Retail Trade
Stryker Corp	0.317	83	Manufacturing
Schlumberger Ltd	0.316	73	Mining, Quarrying, and Oil and Gas Extraction
Conocophillips	0.316	163	Mining, Quarrying, and Oil and Gas Extraction
HCA Healthcare Inc	0.312	63	Health Care and Social Assistance
Marathon Petroleum Corp	0.308	59	Manufacturing
Occidental Petroleum Corp	0.307	69	Mining, Quarrying, and Oil and Gas Extraction
Coca-Cola Co (The)	0.306	258	Manufacturing
Boston Scientific Corp	0.305	61	Manufacturing
PepsiCo Inc	0.303	249	Manufacturing
Chevron Corp	0.301	357	Manufacturing
Berkshire Hathaway Inc	0.300	324	Finance and Insurance
Lockheed Martin Corp	0.299	127	Manufacturing
Boeing Co	0.298	85	Manufacturing
Sherwin-Williams Co (The)	0.296	58	Manufacturing
Activision Blizzard Inc	0.295	57	Information
Pioneer Natural Resources Co	0.294	60	Mining, Quarrying, and Oil and Gas Extraction
Mondelez International Inc	0.292	85	Manufacturing
Northrop Grumman Corp	0.291	82	Manufacturing
Tesla Inc	0.283	719	Manufacturing
Home Depot Inc. (The)	0.261	303	Retail Trade
United Parcel Service Inc	0.256	123	Transportation and Warehousing
CSX Corp	0.256	61	Transportation and Warehousing
Union Pacific Corp	0.253	121	Transportation and Warehousing
Costco Wholesale Corp	0.252	221	Retail Trade
TJX Companies Inc (The)	0.243	83	Retail Trade
Lowe's Cos Inc	0.238	120	Retail Trade
Walmart Inc	0.235	385	Retail Trade
Target Corp	0.235	76	Retail Trade
Dollar General Corporation	0.212	57	Retail Trade
McDonald's Corp	0.194	201	Accommodation and Food Services
Starbucks Corp	0.119	100	Accommodation and Food Services