Automation and Stock Prices:
The Case of ChatGPT

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Abstract

This study examines the impact of ChatGPT's introduction on stock prices. Following the introduction, firms operating in industries with workforces more substitutable to AI techniques are associated with significantly negative stock returns. We attribute the negative share price reaction to the increased competition from the new technology.

JEL classification: G14; G3; J23, O33

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1. Introduction

Recent studies highlight the importance of artificial intelligence (AI) in shaping labor demand, wages, and corporate policies [see, Acemoglu and Restrepo (2018; 2020) and Bates et al. (2020)]. The consensus is that AI substitutes routine tasks such as data entry, and basic research. As AI and natural language processing (NLP) tools become more sophisticated they even outcompete humans in non-routine activities that involve more complex tasks (Bommarito et al., 2022; Gao et al., 2022). Evidently, new AI technology impacts employment and wages, but our knowledge on how the introduction of new technology affects share prices is limited.

We aim to fill this gap by examining how AI technologies impact share prices by using the introduction of ChatGPT as a quasi-natural experiment. ChatGPT is a sophisticated NLP chatbot that was widely adopted already at the introduction, resulting in over one million unique users already within the first week (Mollman, 2022). Figure 1 shows that the introduction came as a surprise to the public, and did not initially lead to a spike in Google searches. Instead, it peaked around five days after the launch. To identify the impact of ChatGPT's introduction on share prices, we estimate a difference-in-difference model (Diff-in-Diff) around the event. We create treatment and control groups from Bates et al. (2020) labor AI substitutability measure (LAS). Their measure captures the sensitivity of an industry's work force to new AI technology.

<Figure 1>

To make predictions on the stock market reaction to the introduction of ChatGPT, we develop two competing hypotheses. First, the efficiency hypothesis, firms can cut costs and gain efficiency through the adoption of new technology, where a reduced labor force can produce similar output. Second, the competition hypothesis, the firm's services become redundant due to the competition of the new technology. The efficiency hypothesis predicts a positive share price reaction of the treatment group, while the competition hypothesis predicts a negative share price reaction to the introduction of new technology.

Lending support to the competition hypothesis, we show that the introduction of ChatGPT negatively impacts the share prices of firms with substitutable workforces. We find a -0.2% daily negative abnormal return following ChatGPT's introduction for firms operating in industries most affected by AI. In cross-sectional tests, we find a cumulative abnormal return (CAR) of -1.2% following the announcement.

We add to the understanding on how AI and NLP models transform the competitive landscape and how investors perceive them. Prior studies have focused on AI's impact on wages, employment, expected returns, and financial policy rather than stock market reactions. A big strand of literature focuses on the impact of new technology on employment and wages (Frey and Osborne, 2017; Acemoglu and Restrepo, 2018, 2020; Webb, 2020). Bates et al., (2020) connects work force substitutability to corporate financial policies and find a positive link to financial leverage. Closest to our study, Zhang (2019) argues that firms with a higher share of routine labor holds an option to substitute labor for capital, which leads to lower systematic risk exposure and thus lower expected returns. Differing from prior work, we find that the introduction of new technology instead has adverse share price effects for firms with substitutable workforces, suggesting increased competition from the new technology.

2. Data and method

We extract daily stock return data from CRSP for U.S. listed firms and financials from COMPUSTAT. The event window spans from 9 days before to 9 days after November 30th, 2022, the date ChatGPT was introduced to the public. We use a market model with an estimation window of -252 to -20 prior to the event window to estimate the parameters used to calculate the abnormal stock return (AR). We end up with 130,296 daily firm-day observations.

We construct the treatment group from the Bates et al (2020) and Frey and Osborne (2017) measure of labor AI substitutability (LAS). The measure reflects to which extent existing labour in an industry can be replaced by AI techniques. To create the treatment group, we split the LAS measure at the median (LAS_High). We estimate the following Diff-in-Diff model on firm-day level:

$$\mathrm{AR}_{\mathrm{it}} = \beta_0 + \beta_1 * \mathrm{LAS\_High}_{\mathrm{i}} * \mathrm{Post}_{\mathrm{t}} + \boldsymbol{\beta_{lit}} * \mathbf{CONTROL}_{\boldsymbol{lit}} + \varphi_{\mathrm{i}} + \pi_t + \varepsilon \qquad (1).$$

The dependent variable AR is the abnormal return for stock *I* at day *t*. The main variable of interest is the interaction between the treatment variable (*LAS_High*) and the post-event indicator (Post). The interaction between Post*LAS_High captures the market reactions to the debut of ChatGPT between the treatment and control group. CONTROL is a matrix including: the standard deviation of stock returns in the of last 10 days prior to day *t* (*Sdreturn*), the bid-ask spread (*Spread*), and the logarithm of trading volume (*lnVOLUME*). Φ_{I}, is firm fixed effect and π_t is a day fixed effect. Since we use firm and year fixed effects the main effects of *LAS_High* and *Post* are absorbed by the fixed effects. For robustness, we also use continuous treatment (*LAS*) in model (1).

For robustness purposes, we conduct cross-sectional tests using CAR as the dependent variable. The cross-sectional tests also include firm-level controls for EBIT-to-assets (*ROA*), liabilities-to-assets (*Leverage*),1-year sales growth (Growth), and the natural logarithm of total assets (*Size*).

2.1. Descriptive statistics

Figure 2 plots the CAR for the treatment (*LAS_High*) and the control group (*LAS_Low*) during the event window. The treatment and control groups exhibit similar trends until four days after the introduction of ChatGPT. After four days the spread in CAR between the groups widen. The delay in the market reaction is consistent with the spike in search volume shown in Figure 1. This suggests that ChatGPT initially took the market by surprise, and it took time for investors and the public to comprehend its implications.

<Figure 2>

Panel A of Table 1 shows the descriptive statistics of the diff-in-diff sample. Panel B shows the descriptive statistics of the sample used for cross-sectional analysis.

<Table 1>

3. Analysis

Column (1) of Table 2 shows a test of parallel pre-trends between the treatment and control group. Our findings do not suggest between-group differences in abnormal returns (AR) prior to the introduction to ChatGPT. Column (2) shows the main Diff-in-Diff analysis using the stocks abnormal return (AR) as the outcome variable. When estimating model (1), we are interested in the interaction between LAS_High*Post. A positive interaction would lend support to the efficiency hypothesis, while a negative interaction supports the competition hypothesis. Our findings in Column (2) of Table 2 shows a negative and statistically significant coefficient of LAS_High*Post (-0.002; $p<0.001$). We repeat the exercise in Column (3) but with continuous treatment (LAS) and find a negative and statistically significant coefficient (-0.012; $p<0.001$). Our findings suggest that the firms most impacted by AI technology exhibit negative share price reactions following the introduction of ChatGPT, lending support to the competition hypothesis. Consequently, the stock market views the introduction as a threat instead of an opportunity for firms with more substitutable workforces.

<Table 2>

Next, we perform cross-sectional tests using CAR as the dependent variable over different event windows. Our findings in Table 3 do not alter our prior interpretation, firms with more substitutable workforces exhibit adverse stock market reactions around the introduction of ChatGPT. This holds true both at the 0 to 3 days, 0 to 9 days, and -3 to +9 days event windows. The effect ranges from -0.9% to -1.4%. We also observe that non-significant differences between the treatment and control group for the -3 to 0 days event windows suggesting that the groups exhibit similar pre-trends. In sum, we find support for the competition hypothesis, the introduction of ChatGPT led to negative share price reactions for firms more affected by new AI technology.

<Table 3>

4. Conclusions

We study how new AI technology impacts share prices by using the introduction of ChatGPT as a quasi-natural experiment. We create treatment and control groups from Bates et al. (2020) labor AI substitutability classification (LAS). By comparing the impact on firms more affected by AI relative to less affected firms, we show that the stock market reacts negatively to the introduction of ChatGPT for firms with higher LAS. Our findings suggest that new AI technology increases competition from substitutes rather than enhances efficiency for firms most impacted by AI.

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Figure 1: Google search trends for ChatGPT

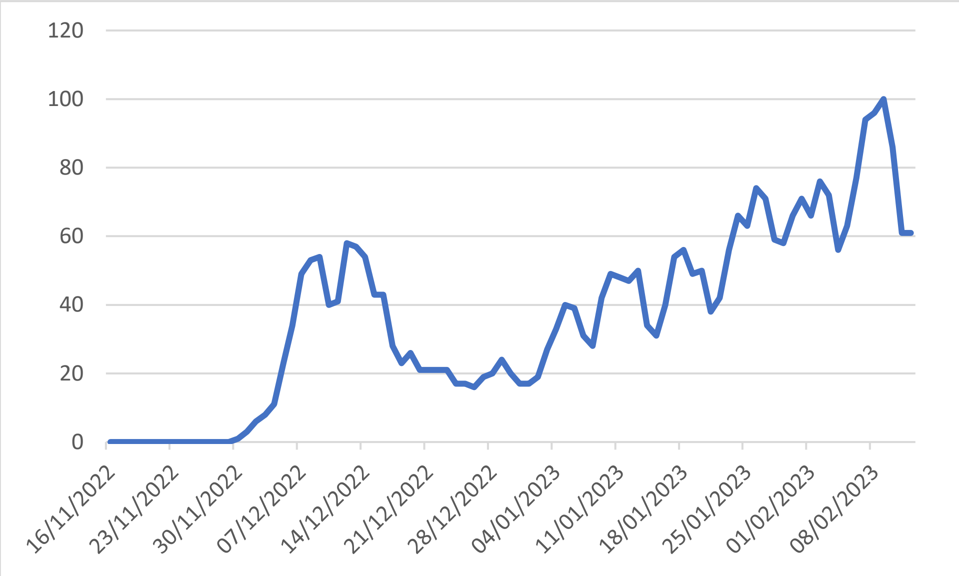

Figure 2: CAR around the introduction of Chat GPT

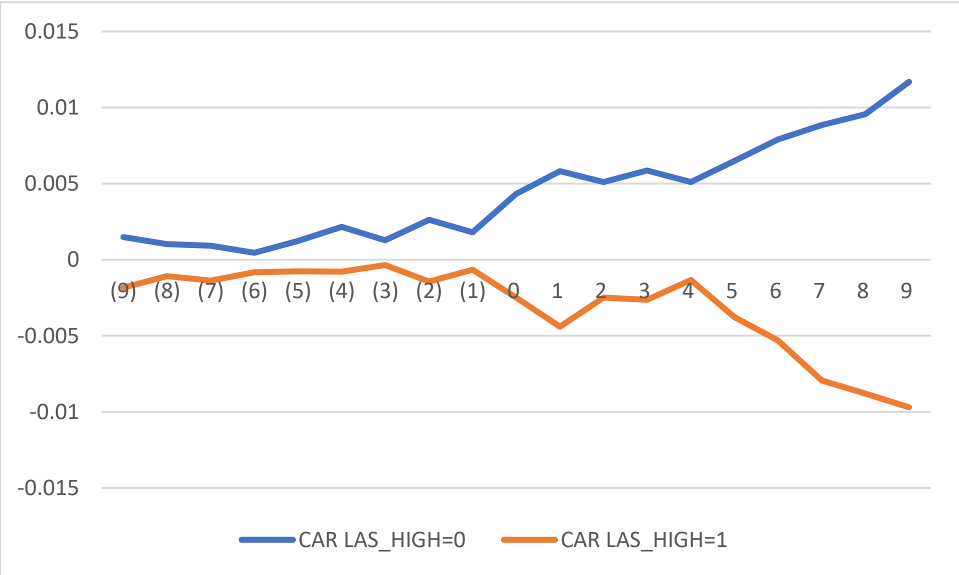

Table 1: Descriptive statistics

This table shows descriptive statistics for the variables included in the diff-in-diff estimation (Panel A), and cross-sectional estimation (Panel B).

Panel A: Variables	N	Mean	SD
AR	130,296	0.000	0.025
LAS_HIGH*Post	130,296	0.141	0.348
LAS*Post	130,296	0.204	0.209
SDreturn	130,296	0.028	0.024
Spread	130,296	0.008	0.014
ln(Volume)	130,296	11.191	2.857

Panel B: Variables	N	Mean	SD
CAR(0,+3)	3,325	0.001	0.055
CAR(0,+9)	3,325	0.003	0.096
CAR(-3,+9)	3,325	0.002	0.106
CAR(-3,0)	3,325	0.000	0.046
LAS_HIGH	3,325	0.259	0.438
ROA	3,325	-0.083	0.292
Sales_Growth	3,325	0.006	0.021
Leverage	3,325	0.216	0.22
Size	3,325	6.083	2.415

Table 2: Diff-in-Diff estimations

This table shows regressions on abnormal stock market return. Column (1) tests for parallel pre-trends for the days -9 to -1. Column (2) shows a difference in difference model with binary treatment (LAS_high), including firms from industries with high AI substitutability of their workforce. Column (3) includes continuous treatment. The main effects in columns (2) and (3) are absorbed by the fixed effects. Heteroskedasticity-robust t-stats based on standard errors clustered by firm are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) AR	(2) AR	(3) AR
LAS_High	0.000		
	(0.396)		
LAS_High*Post		-0.002***	
		(0.001)	
LAS*Post			-0.010***
			(0.000)
SDreturn	-0.074***	-0.188***	-0.189***
	(0.000)	(0.000)	(0.000)
Spread	-0.002	0.001	0.001
	(0.796)	(0.897)	(0.878)
ln(Volume)	-0.000	0.003***	0.003***
	(0.841)	(0.000)	(0.000)
constant	0.002***	0.013	0.059
	(0.000)	(0.457)	(0.252)
Day-FE	Yes	Yes	Yes
Firm-FE	No	Yes	Yes
N	63,080	130,296	130,296
adj.-R-squared	0.006	0.012	0.012

Table 3: Cross-sectional estimations

This table shows regressions on cumulative abnormal stock market returns (CAR) around the introduction of ChatGPT. The variable of interest is LAS_High a binary variable taking the value of one if the firm operates in an industry with high AI substitutability of their workforce. Heteroskedasticity-robust t-stats based on standard errors clustered by firm are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	CAR(0,3)	CAR(0,9)	CAR(-3,9)	CAR(-3,0)
LAS_High	-0.007***	-0.012***	-0.009*	-0.001
	(0.002)	(0.005)	(0.053)	(0.650)
ROA	-0.010*	-0.013	-0.023**	0.005
	(0.064)	(0.190)	(0.034)	(0.277)
Sales_Growth	-0.008	0.019	-0.028	-0.086*
	(0.891)	(0.852)	(0.802)	(0.071)
Leverage	-0.018***	-0.025***	-0.029***	-0.012**
	(0.001)	(0.009)	(0.007)	(0.010)
Size	0.004***	0.013***	0.012***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
SDreturn	0.318***	0.618***	0.720***	0.208***
	(0.000)	(0.000)	(0.000)	(0.000)
Spread	-0.222***	-0.291**	-0.322**	-0.061
	(0.005)	(0.033)	(0.032)	(0.338)
ln(volume)	-0.003***	-0.008***	-0.008***	-0.001
	(0.000)	(0.000)	(0.000)	(0.311)
constant	0.008	-0.004	-0.012	-0.022***
	(0.283)	(0.720)	(0.363)	(0.000)
N	3,325	3,325	3,325	3,325
adj.-R-squared	0.026	0.033	0.030	0.015