The Rise of AI Pricing:

Trends, Driving Forces, and Implications for Firm Performance[*]

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Abstract

We document key stylized facts about the time-series trends and cross-sectional distributions of AI pricing and study its implications for firm performance, both on average and conditional on monetary policy shocks. We use the universe of online job posting data from Lightcast to measure the adoption of AI pricing. We infer that a firm is adopting AI pricing if it posts a job opening that requires AI-related skills and contains the keyword "pricing." At the aggregate level, the share of AI pricing jobs in all pricing jobs has increased by more than tenfold since 2010. The increase in AI pricing jobs has been broad-based, spreading to more industries than other types of AI jobs. At the firm level, larger and more productive firms are more likely to adopt AI pricing. Moreover, firms that adopted AI pricing experienced faster growth in sales, employment, assets, and markups, and their stock returns are also more sensitive to high-frequency monetary policy surprises than non-adopters. We show that these empirical observations can be rationalized by a simple model where a monopolist firm with incomplete information about the demand function invests in AI pricing to acquire information.

Keywords: Artificial intelligence, AI-powered pricing, monetary policy, technology adoption;

JEL Classification: D40, E31, E52, O33

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1 Introduction

Recent advances in artificial intelligence (AI) and other advanced technologies have spurred much interest in understanding the macroeconomic impact of the new technologies and the related policy implications. A lesser-known but no less important area is the rise of AI-powered algorithmic pricing (or AI pricing hereafter). Unlike traditional price-setting technologies, AI pricing algorithms can incorporate a wide range of information and respond to real-time changes in demand and supply conditions. Recent studies have focused on the impact of AI pricing on market competitiveness or collusion outcomes in specific industries, such as online retailing (Aparicio, Eckles, and Kumar, 2023; Wang et al., 2023), housing rental (Calder-Wang and Kim, 2023), gasoline (Clark et al., 2023), and pharmaceutical industries (Brown and MacKay, 2023).

Many important questions related to the rise of AI pricing remain to be investigated. For example, how rapidly has AI pricing grown over time? How widespread has AI pricing been adopted? What types of firms adopt AI pricing? How does AI pricing affect firm performance measured by sales, employment, investment, and markups? How does adopting this new pricing technology change our understanding of price flexibility and monetary policy transmission? Our paper sheds light on these important issues by (i) documenting the time-series trends, cross-industry distributions, and key firm-level determinants of AI pricing, (ii) examining how AI pricing has affected firm performance and its responses to monetary policy shocks, and (iii) presenting a stylized model for understanding the economic mechanism that explains these facts.

We construct a measure of firm-level adoptions of AI pricing using data from Lightcast, which covers nearly the entire universe of online job postings in the U.S. from 2010 onward. We first identify the jobs that require AI-related skills using textual analysis following the approach of Acemoglu et al. (2022b). Within this category of AI-related jobs, we then search for job postings that contain the keyword "pricing" in the job titles, the skill requirements, or the job descriptions. If a job posting specifies both AI-related skills and pricing, then we classify it as a job for AI pricing. We aggregate all AI pricing jobs within a firm in each given period. To examine firm-level determinants of the adoption of AI pricing and the impact of AI pricing on firm performance, we further match our constructed firm-level AI pricing measure from Lightcast with the firm-level balance sheet information from Compustat.

We document the following five stylized facts:

1. AI pricing rose rapidly over time. The share of AI pricing jobs in all pricing jobs has surged by more than tenfold from 2010 to 2024, with the sharpest increases observed after 2016. The rising trend of AI pricing jobs parallels that of all AI-related jobs, resulting in a relatively stable share of AI pricing in all AI jobs. AI jobs account for a relatively small share of

all jobs (with a peak of 0.75% in 2022). In comparison, AI pricing jobs account for a much larger share of all pricing jobs (with a peak of 1.5% in 2022). While the share of AI pricing jobs in all pricing jobs has risen sharply from 2010 to 2024, the share of pricing jobs in all jobs has declined by about 40% during the same period, suggesting that AI pricing may have displaced other pricing jobs.

2. The increase in the share of AI pricing jobs since 2016 has been broad-based, spreading to most industries. In contrast, during the same period, the increase in the share of AI-related jobs in all jobs has been concentrated in a few sectors, mainly in information, manufacturing, finance and insurance, and professional and business services.

3. At the firm level, larger and more productive firms are more likely to adopt AI pricing.

4. The firms that adopted AI pricing are also those firms that experienced faster cumulative growth in sales, employment, total assets, and markups from 2010 to 2023. Those correlations are stronger for larger firms.

5. The stock returns of firms that adopted AI pricing are more sensitive to monetary policy shocks than non-adopters. An expansionary monetary policy surprise—constructed by Bauer and Swanson (2023) using high-frequency data based on FOMC announcements—boosts the stock returns for adopters relative to those of the non-adopters.

To understand the economic mechanism that drives these empirical observations, we construct a simple model where a monopolist firm has incomplete information about the demand function that it faces. The firm produces a single good at a constant marginal cost and sells the good to a continuum of individuals who vary across many observable characteristics. Demand is a high dimensional function of individual observables, and the firm can invest resources into a "pricing technology" to learn about the function. Its learning depends on two types of pricing labor: conventional pricing and AI pricing. AI pricing labor is complementary to computing equipment and a substitute for conventional labor. This complementarity with computing affords AI pricing an economies of scale advantage, compared to conventional pricing. The AI pricing technology also entails a fixed cost, giving rise to a discrete choice of AI adoption.

The model can account for several key stylized facts about the rise of AI pricing observed in the data. Consistent with the time-series evidence, the model predicts that both the adoption rate of AI pricing and the intensity of AI pricing (measured by the share of AI pricing labor) increase over time as computing cost declines. In line with the cross-sectional evidence, the model suggests that larger firms—those with greater revenue–are more likely to adopt AI pricing and use AI pricing more intensively, reflecting the scale economy effects of AI pricing. Moreover, firms with a higher share of AI pricing labor tend to have higher average markups, as they can price discriminate more effectively. Finally, we model monetary policy shocks simply as shifts in aggregate demand. The model predicts that an increase in demand raises gross profits more for firms that do more AI pricing. This aligns with the empirical evidence that AI pricing amplifies the sensitivity of firms' stock returns to monetary policy surprises.

Literature Review. Our paper contributes to the literature in three directions. First, we contribute to the emerging economics literature on artificial intelligence and algorithmic pricing. The focus is usually on how AI pricing changes firms' pricing decisions and market competitiveness in industrial organizations and business.[1] Recently, empirical and quantitative studies have been conducted for many specific industries, including online retailing (Aparicio, Eckles, and Kumar, 2023; Wang et al., 2023), rental (Calder-Wang and Kim, 2023), gasoline (Clark et al., 2023), and medicine (Brown and MacKay, 2023).[2] Our focus is on the adoption of AI pricing across the entire economy: We document the adoption of AI-powered pricing for the universe of US firms posting jobs online and show how such adoption could potentially affect firm performances.

Second, our work is broadly connected to the emerging literature on the macroeconomics of the rise of artificial intelligence. The focus is on how AI, as a new and more efficient technology, would affect various macroeconomic objects, including the labor market (Acemoglu and Restrepo, 2018; Bessen, 2019; Acemoglu et al., 2022b; Leduc and Liu, 2023), economic growth (Aghion, Jones, and Jones, 2019; Jones, 2023; Acemoglu, 2024), income inequality (Korinek and Stiglitz, 2018), market concentration (Tambe et al., 2020; Firooz, Liu, and Wang, 2022), among others. Firm-level surveys (such as the Annual Business Survey by the Census) suggest that the usage of AI and other advanced technologies has been heavily skewed toward large firms (Acemoglu et al., 2022a; McElheran et al., 2024). Our evidence shows that the usage of AI pricing is also concentrated in large and high-productivity firms. Complementary to Babina et al. (2024), who study how general AI investment affects firm performance, we focus on AI as a new price-setting tool and study how AI pricing could affect firm performance, both on average and conditional on monetary policy shocks.

Finally, our paper contributes to the substantial macroeconomics literature on price stickiness. Before the rise of AI pricing, empirical studies show that prices were quite sticky until the mid-2010s. For example, Bils and Klenow (2004) and Nakamura and Steinsson (2008) document that

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[1] Theoretical and simulation works include Calvano et al. (2020), Klein (2021), Asker, Fershtman, and Pakes (2024), Cho and Williams (2024), Brown and MacKay (2024), etc. Also, see Spann et al. (2024) for a detailed survey on various implications and challenges of algorithmic pricing for consumers, managers, and regulators.

[2] Although their focus is mainly on market competitiveness changes or collusion outcomes due to AI pricing, most of these studies show that prices adjust extremely frequently when AI pricing is adopted for specific industries. Using high-frequency online retailing data, Leung, Leung, and Zhou (2023) provides valuable detailed patterns of pricing and price stickiness by online sellers but, unfortunately, cannot exactly confirm AI pricing adopters.

offline prices for major goods and services are very sticky, and Cavallo (2017), Cavallo (2018), and Gorodnichenko, Sheremirov, and Talavera (2018) find that online prices are as sticky as offline prices. Gorodnichenko and Weber (2016) shows that stick prices are costly such that firms with more flexible prices have lower stock market return volatility upon monetary shocks. The rise of AI pricing might fundamentally affect the frequencies and magnitudes of price adjustments, with implications for firms' performance and responses to monetary policy. We show that AI pricing increases the sensitivity of firms' stock returns, and this is true even after we control price adjustment frequencies.

Layout. The rest of the paper is organized as follows. Section 2 documents the economy-wide rise of AI-powered pricing using the universe of job postings from Lightcast. Section 3 merges the job postings to firms' balance sheets and analyzes the determinants of AI pricing adoption. Section 4 examines how AI pricing adoption affects firm performance and monetary policy shocks transmission to firm performance. Section 5 lays out the model and explores its predictions. Section 6 concludes.

2 The Rise of AI Pricing

In this section, we document the rise of AI-powered pricing (AI pricing for short). We examine our constructed measures of AI pricing adoption by identifying leading firms, documenting the aggregate trend over time, and displaying the distribution across industries. We also validate that our measure of AI-related job postings is consistent with findings in previous literature.

2.1 Lightcast Data

We use the Lightcast data, formerly Burning Glass, on U.S. job postings from 2010Q1 to 2024Q1. Lightcast collects job posting data from over 40,000 online job boards and company websites, converting them into a systematic machine-readable form. This dataset covers nearly the entire universe of online vacancies in the U.S. from 2010 onward, representing approximately 60–70% of all job vacancies, both online and offline. The company employs a sophisticated deduplication algorithm to avoid double-counting vacancies posted on multiple job boards. The representativeness of Lightcast data is stable over time at the occupation level. Acemoglu et al. (2022b) confirmed that the total vacancies in Lightcast are consistent with the Job Openings and Labor Turnover Survey (JOLTS), and its distribution across industries and occupations aligns with both JOLTS and Occupational Employment Statistics (OES).

The main advantage of using Lightcast is its detailed text information for each job posting, including job title, job location, occupation, employer name, specific skills required, and job description. Following the approach in Acemoglu et al. (2022b) and Babina et al. (2024), we detect AI-powered pricing vacancies by identifying postings that require AI-related skills and mentioning the keyword "pricing". This helps us identify businesses engaging in AI pricing activities, as AI-skilled pricing teams are crucial for implementing AI pricing. Our analysis focuses on the firm level, as pricing algorithms are typically developed and applied at the firm rather than at the establishment level. We first identify all AI-related and pricing job postings to measure firm-level AI pricing adoption. AI pricing postings are those at the intersection of these two groups. We then calculate the share of AI pricing postings among all pricing postings for each firm.

2.2 AI-Powered Pricing Measures

To construct our measures on the intensity of AI pricing, we need to extract AI-related jobs, pricing jobs, and AI-related pricing jobs from all job postings. To define AI-related job postings, we follow exactly Acemoglu et al. (2022b)'s narrow category classification, focusing on advanced technology such as machine learning and AI chatbots.[3] This narrow category measure avoids capturing traditional pricing information technology functions such as office software, software as a service (SaaS) pricing models, or data analysis, which are separate from core AI activities.

We then identify pricing jobs based on the keyword "pricing." In particular, for each job posting, we search for the keyword "pricing" in the job title, the job skill requirements, and the job descriptions. Focusing on the keyword "pricing" mitigates concerns about capturing traditional pricing jobs such as sales and marketing in the pricing measure. For robustness, we also consider three alternative scopes of pricing jobs. The first scope includes only those that contain the keyword "pricing" in the job title. The second scope includes those with the keyword "pricing" in the job skill requirements but not in the title. The third scope includes jobs with the keyword "pricing" in the main body of the job descriptions but not in the title or the skill requirements.

Finally, we identify AI pricing job postings as the intersection of AI-related and pricing jobs. Table 1 summarizes these job postings at the firm level at the monthly frequency.

With these measures, we could construct a panel of job postings for firm j at time t. The measures include the number of jobs posted $N_{j,t}$, the number of AI jobs posted $N_{j,t}^{AI}$, the number of pricing jobs posted $N_{j,t}^{P_s}$ for each scope $s = \{1, 2, 3, all\}$, and the number of AI pricing jobs $N_{j,t}^{AP_s}$ for

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[3] The full list of AI-related skills includes machine learning, computer vision, machine vision, deep learning, virtual agents, image recognition, natural language processing, speech recognition, pattern recognition, object recognition, neural networks, AI chatbot, supervised learning, text mining, unsupervised learning, image processing, Mahout, recommender systems, support vector machines, random forests, latent semantic analysis, sentiment analysis/opinion mining, latent Dirichlet allocation, predictive models, kernel methods, Keras, gradient boosting, OpenCV, XGBoost, Libsvm, Word2vec, machine translation, and sentiment classification.

Table 1: Summary Statistics of Firm-Level Lightcast Job Postings

Job Type	Total	Mean	Std.Dev.	Min	Max
All Jobs	3.39e+08	13.32918	189.1815	1	147846
Pricing Jobs	2662686	0.1047685	5.465651	0	6905
AI Jobs	1614194	0.0635136	2.837486	0	2835
AI pricing jobs	24461	0.0009625	0.1236612	0	149
Observations	25414949	*Firm-Level at Monthly Frequency*			

Notes: This table summarizes our Lightcast Job Posting Data from 2010Q1 to 2024Q1. We follow the narrow category classification of Acemoglu et al. (2022b) to define AI-related job postings. We extract pricing jobs in three scopes: the keyword "pricing" in the job title (Scope 1), in their specific job skill requirements (Scope 2), and in the main body of the job description (Scope 3). We define AI pricing job postings as the intersection of AI-related and pricing jobs across all three scopes.

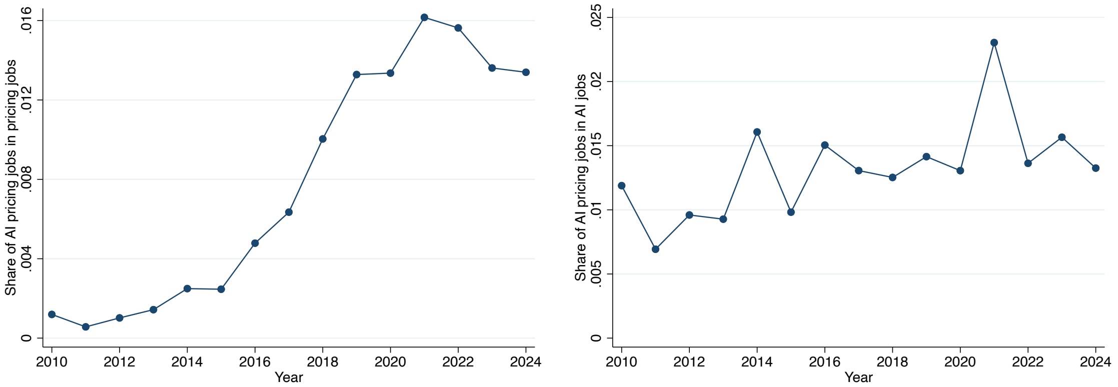
each scope $s = \{1, 2, 3, all\}$. We then compute firm-level intensity measures ($Share_{j,t}^{x/y} = N_{j,t}^{x}/N_{j,t}^{y}$) for firm j of x over y at different time frequencies $t = \{yearly, quarterly\}$ to meet our various regression specifications. Our primary focus is on the intensities of AI-related pricing jobs within pricing jobs ($Share_{j,t}^{AP_s/P_s}$) for all scopes together.

2.3 Aggregate Trends

First, we document that the share of AI pricing job postings has risen sharply over time, increasing more than ten times from 2010 to 2024. Panel (a) of Figure 1 shows the fraction of all-scope pricing job postings that we classify as AI-related: this fraction starts at 0.12% in 2010 and reaches 1.34% in 2024Q1. The trend peaked at 1.56% in 2022 and then slightly decreased. The trend is consistent across different scopes of pricing job measures.

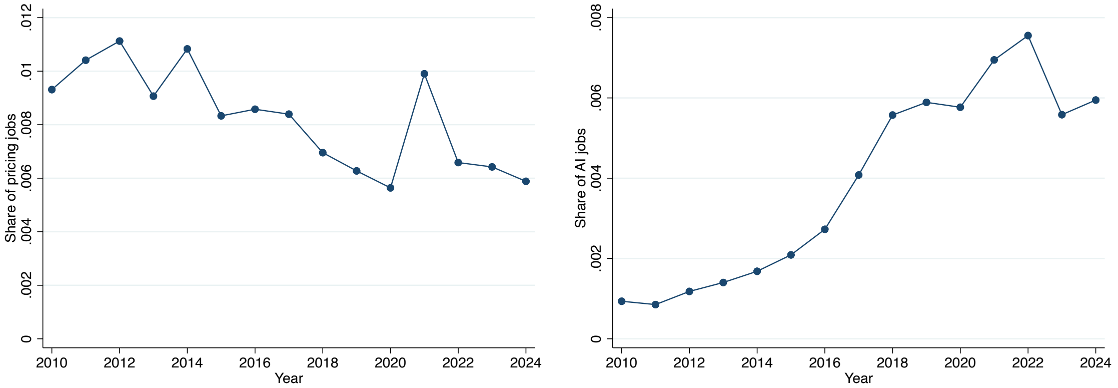
We then validate the external environment for the rise of AI pricing job postings by checking the changes in the fractions of AI pricing jobs in AI jobs and the fractions of pricing jobs in all jobs, respectively. Panel (b) shows that the fraction of AI pricing jobs in all AI-related jobs is relatively stable (with a spike in 2021) but overall increases by about 10%: this fraction starts at 1.19% in 2010 and reaches 1.33% in 2024Q1. Panel (c) shows that the fraction of pricing jobs in all jobs is relatively stable (with a spike in 2021 as well) but overall decreases by about 40%: this fraction starts at 0.93% in 2010 and reaches 0.59% in 2024Q1. In both fractions, we see spikes in 2021, which signals a high demand for labor in AI pricing and pricing. Again, the trends are consistent across different job pricing measures. Finally, Panel (d) confirms that our AI job posting measure is consistent with the literature, showing a rapidly growing trend as documented in Acemoglu

Figure 1: Aggregate Time Trends of AI Pricing, Pricing, and AI Jobs



(a) Share of AI Pricing in Pricing Jobs

(b) Share of AI Pricing in AI Jobs



(c) Share of Pricing Jobs in All Jobs

(d) Share of AI Jobs in All Jobs

Notes: This figure plots the aggregate time trends of AI pricing, pricing, and AI jobs, measured in different shares and scopes at annual frequency. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs are measured in three scopes. The first scope only includes the most narrowly defined pricing jobs, which must include exactly the keyword "pricing" in its job title. The second scope includes jobs with the keyword "pricing" in their specific job skill requirements. Finally, the third scope includes jobs with the keyword "pricing" in the main body of the job description, which is the most broadly defined pricing jobs. We combine all three scopes to generate an all-scope measure. Finally, we extract AI pricing jobs at the intersection of both AI-related and pricing jobs in all three scopes. With all these measures, we could construct a penal of job postings for firm j at time t. The measures include the number of jobs $N_{j,t}$, the number of AI jobs $N_{j,t}^{AI}$, the number of pricing jobs $N_{j,t}^{P_s}$ with scope $s = \{1, 2, 3, all\}$, and the number of AI pricing jobs $N_{j,t}^{AP_s}$ with scope $s = \{1, 2, 3, all\}$. We aggregate all measures to the firm level $Share_{j,t}^{x/y} = N_{j,t}^{x}/N_{j,t}^{y}$. Robustness checks of alternative measures of three scopes separately are presented in Figure A4.

et al. (2022b) and Babina et al. (2024) up to 2018, followed by a tech labor market downturn around 2022.

Third, AI pricing appears to play an important role compared to other AI jobs or non-AI pricing jobs. First, although AI jobs constitute a relatively small fraction of total job postings, with a peak of 0.75% in 2022, AI pricing jobs account for a much larger fraction of total pricing postings, with a peak of 1.5% in 2022. Second, along with the rise of AI pricing job postings, the stable decline of overall pricing jobs signals the potential replacement of non-AI pricing jobs by AI pricing jobs. From 2010 to 2024Q1, the share of AI pricing job postings in all job postings increases by 0.0068% from 0.0011% (0.12%×0.93%) to 0.0079% (1.34%×0.59%) while the share of pricing job postings in all job postings decreases by 0.34% from 0.93% to 0.59%. If we assume the total number of pricing tasks is a constant share of the economy, then the back-of-envelope calculation infers that one AI pricing worker could replace fifty non-AI pricing workers.

2.4 Variations Across Industries

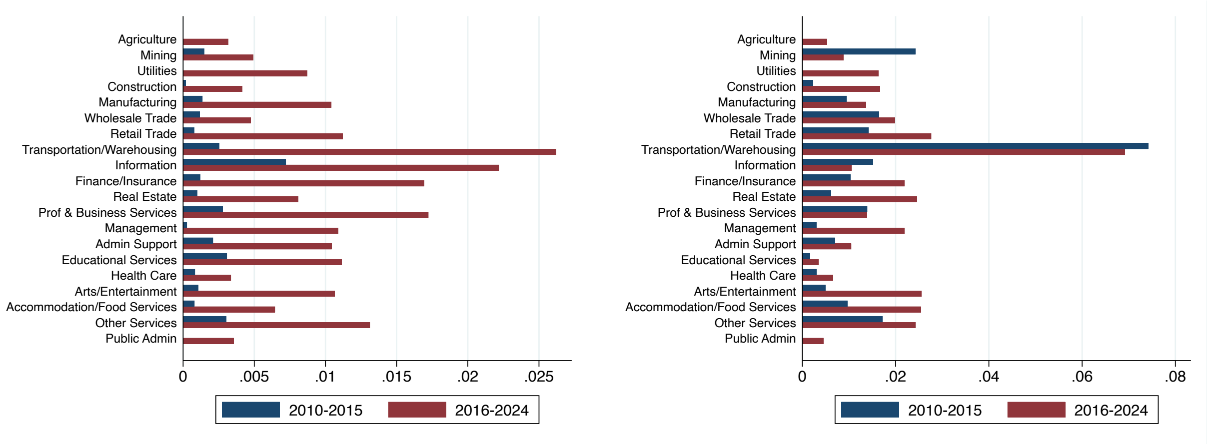
Third, we document that the increase in AI pricing job postings varies significantly across industries, and the evolution of its distribution differs from that of pricing job postings and AI-related job postings. Figure 2 shows the variations in the share of AI pricing jobs across industries over time, using 2-digit NAICS sectors. The data is split into two periods: 2010–2015 and 2016–2024. We use 2015 as the cutoff since Figure 1 shows a clear acceleration in AI pricing after this year, consistent with the surge in AI jobs and the cutoff used in Acemoglu et al. (2022b).

Panel (a) plots the average share of AI-related pricing job postings in each sector for the periods 2010–2015 and 2016–2024. It reveals that the shares of AI pricing job postings among all pricing job postings increased across all sectors after 2015. The information sector had the highest share of AI pricing jobs among pricing jobs at 0.7% before 2015, which increased to 2.2% after 2015. However, the transportation sector surpassed it after 2015, with a share exceeding 2.5%. The finance industry also saw a significant rise from nearly zero in 2010-2015 to 1.7% in 2016-2024, one of the highest shares. In contrast, industries such as agriculture, mining, and construction maintained consistently low shares of AI pricing jobs across both periods, indicating limited applicability or slower adoption of AI in pricing within these sectors.

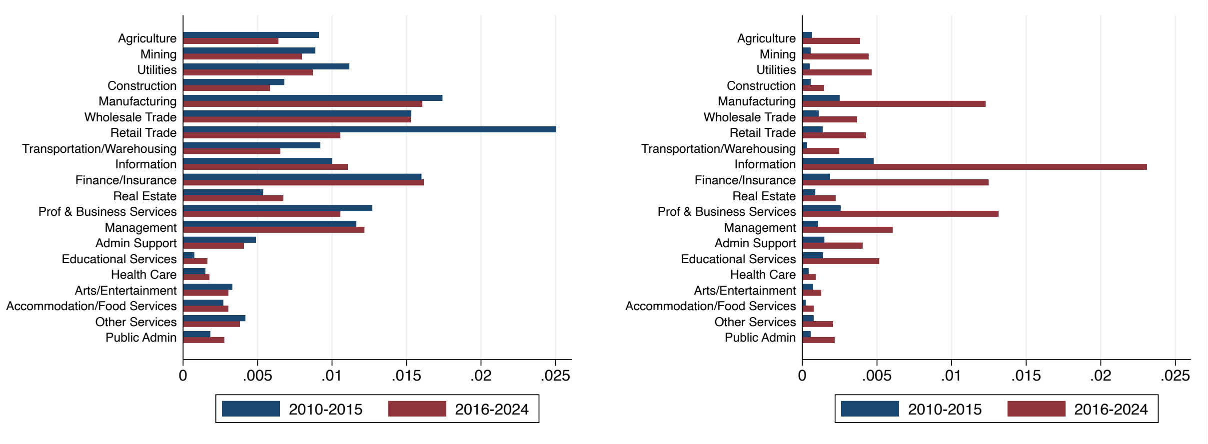
As a comparison, Panel (c) shows the share of pricing job postings among all job postings across industries. Most sectors exhibited stable shares, with either slight increases or decreases. The most significant change occurred in the retail trade sector, where the average share of pricing job postings dropped from 2.5% in 2010-2015, the highest at that time, to around 1.1% in 2016-2024. Given that Panel (a) shows a substantial increase in AI pricing postings among all pricing-related postings, this may suggest a strong substitution of non-AI pricing jobs with AI pricing jobs in the retail trade sector.

On the other hand, Panel (b) reveals substantial variation in the ratios of AI pricing postings

Figure 2: Variations Across Two Digit Industry Sector



(a) Share of AI Pricing in Pricing Jobs (b) Share of AI Pricing in AI Jobs



(c) Share of Pricing Jobs in All Jobs (d) Share of AI Jobs in All Jobs

Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs, measured in different shares and scopes for two periods: 2010-2015 and 2016-2024. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs are measured in three scopes. The first scope only includes the most narrowly defined pricing jobs, which must include exactly the keyword "pricing" in its job title. The second scope includes jobs with the keyword "pricing" in their specific job skill requirements. Finally, the third scope includes jobs with the keyword "pricing" in the main body of the job description, which is the most broadly defined pricing jobs. We combine all three scopes to generate an all-scope measure. Finally, we extract AI pricing jobs at the intersection of both AI-related and pricing jobs in all three scopes. With all these measures, we could construct a penal of job postings for firm j at time t. The measures include number of jobs $N_{j,t}$, number of AI jobs $N_{j,t}^{AI}$, number of pricing jobs $N_{j,t}^{P_s}$ with scope $s = \{1, 2, 3, all\}$, and number of AI pricing jobs $N_{j,t}^{AP_s}$ with scope $s = \{1, 2, 3, all\}$. We aggregate all measures to the firm level $Share_{j,t}^{x/y} = N_{j,t}^{x}/N_{j,t}^{y}$. To plot the bar plots, we combine all job postings within the two periods, 2010-2015 and 2016-2024.

to all AI postings across sectors. Although these ratios generally increase across industries, the magnitudes are relatively small due to the significant overall rise in AI postings over time (Panel (d)). The transportation and warehousing sector consistently holds the highest ratio of AI pricing postings to all AI postings before and after 2015, but its ratio slightly decreased from 0.75% to 0.7%, likely due to its already high level before 2015. Notable increases in this ratio are observed in the construction, finance, real estate, management, and entertainment industries, indicating a significant shift towards pricing-related AI technologies within these sectors.

Panel (d) displays the distribution of AI job posting shares across industries, showing significant increases with considerable heterogeneity. The distribution of AI pricing postings differs from the overall share of AI postings (Panel (b)). The information sector has the largest share of AI-related vacancies, around 2.3%, from 2016 to 2024. In contrast, AI pricing has become more prevalent and has grown rapidly in broader industries, including transportation, IT, business services, finance, and retail. This difference may be because the IT sector is the primary provider of AI technologies, which are applied in pricing across various other sectors.

2.5 Case Studies and Robustness Checks

Our case studies of leading firms in Online Appendix A.2 show clear transition paths in the advancements of AI pricing. They all started with simple rule-based pricing in the early 2010s, transitioned to algorithmic dynamic pricing around 2015, and then advanced to more sophisticated algorithmic pricing by the late 2010s. They finally adopted behavioral, contextual, and real-time pricing starting in the 2020s. We also perform various robustness checks for leading firms in Online Appendix A.4 and A.5 and examine industry variations with different scopes in Online Appendix A.6. The list of leading firms and the variations across industries remain consistent, even when the AI pricing measure is broken down into three scopes.

3 Firm-level Determinants of AI pricing Adoption

Given the heterogeneity described above, what determines a firm's adoption of AI pricing? We next examine the firm-level determinants of AI pricing adoption, and we find that larger, more productive firms tend to adopt AI pricing more aggressively.

3.1 Merge to Compustat Quarterly Dataset

To obtain firm characteristics such as size, age, productivity, and financial conditions, we merge the Lightcast data with Compustat Quarterly. Compustat Quarterly provides detailed balance sheet data for the universe of public US firms. We use the crosswalk provided by Lightcast to link the firm ID in Lightcast to the Global Company Key (gvkey) in Compustat. Additionally, we verify firm names and addresses to remove duplicates from the crosswalk. This process results in a quarterly panel dataset with 4,695 unique firms and 131,647 firm-quarter observations.

Table 2: Summary of Lightcast & Compustat Quarterly Merged Sample

Variables	Obs.	Mean	Std.Dev.	Min	Max
$\mathbb{1}^{AP}_{j,t}$	131647	0.17	0.37	0	1
$APN_{j,t}$	131647	3.79	32.69	0	1177
$APS_{j,t}$	107452	0.01	0.05	0	1
Log Sales	129240	5.32	2.10	-7	12
Log TFP	113178	0.07	0.91	-8	6
Log Age	122189	3.07	0.84	0	5
Tobin's Q	131276	0.55	0.59	-2	4
Log Markup	128637	0.63	0.95	-11	9
R&D/Sales	62880	6.21	205.65	-3937	31684
ROA	131331	0.03	0.08	0	13
Cash/Asset	131403	0.19	0.22	0	1
Debt/Asset	122077	0.26	0.26	0	9

Notes: This table summarizes our Lightcast Job Posting Data merged with Compustat Quarterly from 2010Q1 to 2024Q1. The balance sheet variables are winsorized at the top and bottom 1%. The three measures of AI pricing adoption are constructed as follows. First, we construct a dummy indicator of AI pricing adopter $\mathbb{1}^{AP}_{j,t}$ which equals one if firm j posted at least one AI pricing job since the beginning of our data sample until time t. Second, we construct a total number indicator of AI pricing job posting numbers $APN_{j,t}$, which sums up firm j AI pricing job postings from the beginning of our data sample until time t. Finally, we construct an intensity indicator of AI pricing job posting as a share of pricing job posting $APS_{j,t}$, which divides the above total number indicator of AI pricing job posting numbers $APN_{j,t}$ by the total number indicator of pricing job posting numbers. We use cumulative rather than periodic measures to avoid noises caused by large short-run fluctuations in job postings.

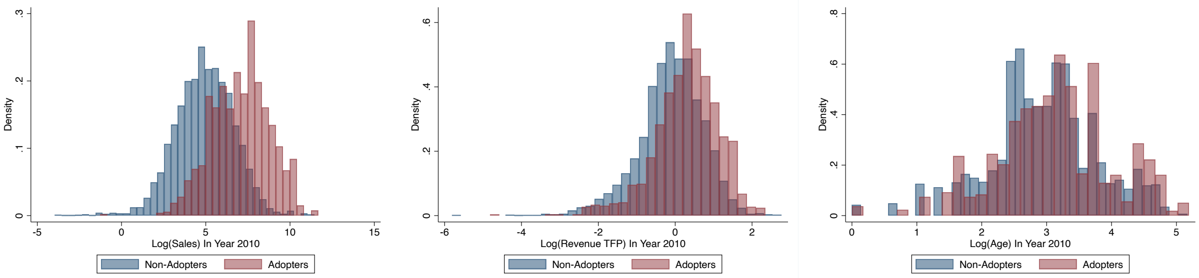
For each firm, we construct three measures of AI pricing adoption. First, we construct a dummy indicator of AI pricing adopter $\mathbb{1}^{AP}_{j,t}$ which equals one if firm j posted at least one AI pricing job since the beginning of our data sample until time t. Second, we construct a total number indicator of AI pricing job posting numbers $APN_{j,t}$, which sums up firm j AI pricing job postings from the beginning of our data sample until time t. Finally, we construct an intensity indicator of AI pricing job posting as a share of pricing job posting $APS_{j,t}$, which divides the above total number indicator of AI pricing job posting numbers $APN_{j,t}$ by the total number indicator of pricing job posting numbers. We use cumulative rather than periodic measures to avoid noises caused by large short-run fluctuations in job postings. Table 2 provides the summary statistics.

3.2 Distributions of Adopters and Non-Adopters

We begin by examining the initial characteristics of firms that posted AI pricing jobs (adopters) and those that never posted AI pricing jobs (non-adopters) from 2010 to 2024Q1. The three panels of Figure 3 compare the distributions of sales, total factor productivity (TFP), and age for adopters and non-adopters in 2010, the first year in our sample. Both sales and TFP are winsorized at the top and bottom 1% at the quarterly frequency.

Figure 3 panel (a) shows that the histogram of log-transformed sales for adopters is shifted to the right, indicating that adopters generally have higher sales than non-adopters. Panel (b) depicts the distribution of logged TFP in 2010 for the two groups of firms. To calculate TFP, we first obtain value-added by subtracting the cost of goods sold from sales. We then regress the logged value-added on capital and labor, using the residuals as the logged revenue TFP. Panel (b) reveals a similar pattern: adopters have higher TFP values, suggesting that more productive firms are more likely to post AI pricing vacancies. Panel (c) plots the distribution of logged firm age in 2010. Firm age is calculated as the difference between the current date and the date of incorporation obtained from Datastream. We observe that adopters tend to be older on average compared to non-adopters, though the difference is less pronounced than the size and TFP distributions.

Figure 3: Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



(a) Size Distribution

(b) TFP Distribution

(c) Age Distribution

Notes: An adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 1$) is a firm j that posted at least one AI pricing job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 0$) is a firm j that never posted AI pricing job since the beginning of our data sample until 2024Q1. We provide a comparison to AI adoption in Figure B4.

3.3 Firm-Level Determinants of AI pricing Adoption

Next, we run OLS regressions to test whether the ex-ante characteristics of firms can predict their AI pricing adoption decisions. Following Babina et al. (2024), we consider the regression specification

$$\mathbb{1}^{AP}_{j,2024Q1} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq}, \tag{1}$$

where j represents firms, q is one of the four quarters, and s refers to two-digit NAICS sectors. The dependent variable, $\mathbb{1}^{AP}_{j,2024Q1}$, is firm j's AI pricing adoption indicator, which equals one if the firm posts at least one AI pricing vacancy between 2010Q1 and 2024Q1. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$. The characteristics examined include logged sales, logged TFP, logged age, Tobin's Q, logged markup, the ratio of R&D to sales, ROA, cash-to-assets ratio, and debt-to-assets ratio, all winsorized at the top and bottom 1% at the year quarter frequency.[4] We also include industry fixed effects (γ_s) and quarter fixed effects (δ_q) to control for unobserved heterogeneity.

Table 3 reports the regression results for our coefficient of interest β. The first three columns confirm our previous findings that larger, more productive, and older firms are more likely to adopt AI pricing technology. Columns (4) and (5) show that Tobin's Q and log markup are also positively associated with AI pricing adoption, suggesting that firms with higher evaluation and higher pricing power are more likely to adopt AI pricing. Column (6) indicates that the R&D to sales ratio is insignificant on its own. Conversely, ROA and cash-to-assets ratio in Columns (7) and (8) show negative correlations with AI pricing adoption, indicating that firms with higher profitability and liquidity are less likely to adopt AI pricing. In Column (9), the debt-to-assets ratio has a significant positive coefficient, suggesting that firms with higher leverage are more likely to adopt AI pricing.

In Column (10), we pool all explanatory variables to run a "horse-race" regression. The variables that remain significant are sales, TFP, and the R&D to sales ratio. Log sales have a coefficient of 0.109, indicating that a 10% increase in sales is associated with a 1.09% higher probability of adopting AI pricing, controlling for other firm characteristics. Log TFP has a coefficient of 0.024, suggesting that a 10% increase in TFP is related to a 0.24% higher likelihood of AI pricing adoption. Unlike the single-variable regression in Column (6), the R&D to sales ratio shows a highly significant positive correlation, with a coefficient of 0.351, indicating that a 10% increase in R&D investment corresponds to a 3.51% higher probability of AI pricing adoption. Although included, other variables such as log age, Tobin's Q, log markup, ROA, cash-to-asset ratio, and debt-to-assets ratio are insignificant in this pooled regression.

In addition to using a dummy dependent variable for the AI pricing adopter dummy, we also run regressions for total AI pricing job postings and AI pricing job postings as a share of total

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[4] Tobin's Q is calculated as tobinq = (prccq × cshoq − ceqq + atq)/atq, where the market value of the firm's assets (prccq × cshoq) is adjusted by subtracting the book value of equity (ceqq) and adding total assets (atq), then divided by total assets (atq). Makrup is calculated as the ratio of sales to costs of goods sode.

Table 3: Firm-level Determinants of AI pricing adoption

	AI Pricing Adopter Dummy Indicator, 2010-2024Q1 ($\mathbb{1}^{AP}_{j,2024Q1} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.089***									0.109***
	(0.002)									(0.004)
Log TFP 2010		0.103***								0.024**
		(0.006)								(0.012)
Log Age 2010			0.032***							0.007
			(0.005)							(0.008)
Tobin's Q 2010				0.011***						0.006
				(0.003)						(0.004)
Log Markup					0.016**					0.009
					(0.007)					(0.016)
R&D/Sales 2010						-0.000				0.351***
						(0.000)				(0.065)
ROA 2010							-0.225***			0.130
							(0.081)			(0.136)
Cash/Assets 2010								-0.104***		0.020
								(0.023)		(0.042)
Debt/Assets 2010									0.071***	-0.013
									(0.020)	(0.037)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	3790	7776	7787	7299	3021
adj. R^2	0.205	0.060	0.022	0.018	0.017	0.021	0.017	0.004	0.002	0.239

Note: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The data sample is from 2010Q1 to 2024Q1 at the quarterly level. The regression specification is $\mathbb{1}^{AP}_{j,2024Q1} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq}$, where j represents firms, q is one of the four quarters, and s refers to two-digit NAICS sectors. The dependent variable, $\mathbb{1}^{AP}_{j,2024Q1}$, is firm j's AI pricing adoption indicator, which equals one if the firm posts at least one AI pricing vacancy between 2010Q1 and 2024Q1. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$.

pricing job postings. The specifications are as follows:

$$\{APN_{j,2024Q1}, APS_{j,2024Q1}\} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq},$$

where all the other specifications are the same as regression specification (1).

In Table 4, we replace the dependent variable in regression specification (1) with firms' total AI pricing job postings from 2010Q1 to 2024Q1 ($APN_{j,2024Q1}$). The results are consistent with the previous findings: Column (10) of Table 4 shows that firms with more sales, higher TFP, or a higher R&D-to-sales ratio post more AI pricing vacancies. Lastly, we change the dependent variable to the ratio of total AI pricing job postings to total pricing job postings from 2010Q1 to 2024Q1 ($APS_{j,2024Q1}$), reflecting AI pricing job postings intensity. Table 5 displays the regression results. Focusing on Column (10), we find that log sales lose explanatory power, while log TFP still

Table 4: Firm-level Determinants of Cumulative AI pricing job Postings

	Total AI pricing job Postings, 2010-2024Q1 ($APN_{j,2024Q1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	3.754***									4.413***
	(0.210)									(0.434)
Log TFP 2010		5.485***								3.232***
		(0.547)								(1.128)
Log Age 2010			1.417***							0.367
			(0.502)							(0.813)
Tobin's Q 2010				1.126***						0.271
				(0.291)						(0.426)
Log Markup 2010					0.594					-2.457
					(0.627)					(1.578)
R&D/Sales 2010						-0.007				12.475**
						(0.031)				(6.298)
ROA 2010							-8.341			3.730
							(7.489)			(13.223)
Cash/Assets 2010								1.962		6.235
								(2.134)		(4.094)
Debt/Assets 2010									1.721	-4.315
									(1.388)	(3.553)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	3790	7776	7787	7299	3021
adj. R^2	0.053	0.028	0.016	0.016	0.014	0.016	0.014	0.014	0.007	0.060

Note: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The data sample is from 2010Q1 to 2024Q1 at the quarterly level. The regression specification is $APN_{j,2024Q1} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq}$, where j represents firms, q is one of the four quarters, and s refers to two-digit NAICS sectors. The dependent variable, $APN_{j,2024Q1}$, is firm j's AI pricing adoption indicator, which is the total AI pricing vacancy posted between 2010Q1 and 2024Q1. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$.

has a significantly positive correlation with AI pricing adoption intensity. Conversely, age now shows a significant negative coefficient, implying that younger firms are more likely to intensify their AI job postings among pricing postings. The coefficient for log markup is significantly negative, indicating that firms with pricing power are less likely to intensify their AI pricing job postings. The R&D to sales ratio has a positive coefficient, with a coefficient of 0.022, though it is only marginally significant. Lastly, the debt-to-assets ratio has significantly positive explanatory power, suggesting that firms with higher leverage are more likely to have a greater intensity of AI pricing job postings.

Table 5: Firm-level Determinants of Cumulative AI pricing job Postings Intensity

	Total AI pricing job Postings/Total Pricing Job Postings, 2010Q1-2024Q1 ($APS_{j,t}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.001***									0.000
	(0.000)									(0.001)
Log TFP 2010		0.004***								0.007***
		(0.001)								(0.002)
Log Age			-0.002***							-0.004***
			(0.001)							(0.001)
Tobin's Q 2010				0.001***						-0.000
				(0.000)						(0.001)
Log Markup 2010					0.001					-0.007***
					(0.001)					(0.003)
R&D/Sales 2010						-0.000				0.022*
						(0.000)				(0.011)
ROA 2010							0.008			-0.012
							(0.017)			(0.032)
Cash/Assets 2010								0.008**		-0.003
								(0.004)		(0.008)
Debt/Assets 2010									0.003	0.022***
									(0.003)	(0.006)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	6229	5826	5925	6238	6215	3047	6232	6240	5875	2552
adj. R^2	0.010	0.012	0.012	0.011	0.009	0.007	0.009	0.010	0.010	0.019

Note: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The data sample is from 2010Q1 to 2024Q1 at the quarterly level. The regression specification is $APS_{j,2024Q1} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq}$, where j represents firms, q is one of the four quarters, and s refers to two-digit NAICS sectors. The dependent variable, $APS_{j,2024Q1}$, is firm j's AI pricing adoption indicator, which is the total AI pricing vacancy posted between 2010Q1 and 2024Q1 divided by the total pricing vacancy posted during the same period. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$.

3.4 Robustness Checks

We check various distributions of the determinants of AI pricing adoption in Online Appendix B.1, provide comparisons with AI adoption in Online Appendix B.2, and run sub-period regressions of specification (1) in Online Appendix B.3. We find the adoption patterns of AI pricing are consistently significant in size and productivity but not consistently significant in other measures.

4 AI pricing Adoption and Firm Performance

Next, we examine how AI pricing adoption is correlated to firm performance. We first document that firms' adoption of AI pricing positively correlates to faster sales, employment, and market value growth. We consider and rule out alternative explanations for this result, including reverse causality and omitted variables using long differences. Then, we show how firms' adoption of AI pricing affects monetary policy shock transmission to their stock return in externally identified high-frequency FOMC announcement events.

4.1 Long-differences Results

We begin the analysis by examining whether firms that hire a larger share of AI-powered pricing workers in their pricing teams see faster growth over time. To explore this, we specify a long-differences regression, linking changes in firm outcomes to different indicators of AI pricing adoption. As is standard in settings with slow-moving processes, such as technological progress (i.e., robots in Acemoglu and Restrepo (2020) and AI in Babina et al. (2024)), by taking first differences in independent and dependent variables, the long-differences specification ensures that time-invariant firm characteristics do not drive the results. Accordingly, we run the following regression:

$$\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i \tag{2}$$

where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We do not include 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s is the two-digit NAICS industry fixed effect.

Table 6 shows the estimates for the above regression. In columns 1, 3, 5, and 7, we include only industry fixed effects to examine the unconditional relationship between changes in AI pricing adoption and firm growth. In columns 2, 4, 6, and 8, we add a rich set of controls measured at the start of the sample period in 2010, including (1) the initial firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash-to-asset ratio); and (2) the initial firm-level share of AI workers and share of pricing workers. We also include industry-fixed effects and quarter-fixed effects. This results in a sample of 4,014 firm quarter observations. The results of the regressions without controls are similar when estimated on the entire available sample.

In columns 1 and 2 of Table 6, the dependent variable is the firm-level change in log sales from 2010 to 2023. Changes in AI pricing are associated with a significant and economically meaningful increase in sales growth: a one percentage point increase in the share of AI pricing workers to the whole pricing team over the thirteen-year period corresponds to an additional 0.86% cumulative growth in sales. In columns 3 and 4, we find a positive association with employment growth

Table 6: AI Pricing and Firm Performance: Long-differences

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.193^{***}	0.857^{***}	0.996^{***}	0.559^{**}	1.134^{***}	0.806^{***}	0.259	0.282^{**}
	(0.332)	(0.291)	(0.286)	(0.252)	(0.343)	(0.309)	(0.166)	(0.121)
Share of AI		-0.029		-0.332		-0.237		-0.634^{**}
		(0.663)		(0.570)		(0.706)		(0.277)
Share of Pricing		0.252		0.712^{***}		0.321		-0.035
		(0.188)		(0.243)		(0.201)		(0.079)
Log Sales		-0.088^{***}		-0.098^{***}		-0.107^{***}		0.005
		(0.009)		(0.008)		(0.009)		(0.004)
Log TFP		-0.014		0.118^{***}		-0.013		-0.085^{***}
		(0.020)		(0.018)		(0.021)		(0.008)
Log Age		-0.117^{***}		-0.114^{***}		-0.110^{***}		0.003
		(0.016)		(0.014)		(0.017)		(0.007)
Tobin's Q		0.436^{***}		0.360^{***}		0.684^{***}		-0.032^{**}
		(0.035)		(0.032)		(0.038)		(0.015)
Cash/Assets		0.003		0.173^{*}		-0.291^{***}		0.184^{***}
		(0.103)		(0.095)		(0.110)		(0.043)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4014	3583	3677	3293	4025	3587	4014	3583
adj. R^2	0.064	0.184	0.086	0.228	0.049	0.201	0.018	0.054

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

similar to the relationship with sales but with a smaller magnitude. Columns 5 and 6 show that firms adopting AI pricing also increase total assets to a smaller magnitude. Finally, in columns 7 and 8, we show it is potentially because firms using AI pricing could charge a higher markup: a one percentage point increase in the share of AI pricing workers to the whole pricing team over the thirteen-year period corresponds to an additional 0.28% cumulative growth in markup. Including firm-level and industry-level controls has small effects on the magnitude of the estimated coefficients, with the exception of the markup regression, for which the estimated coefficient on the growth of the share of AI pricing jobs turns from insignificantly different from zero to significant at the 95 percent confidence level. Thus, it is unlikely that the results are driven by ex-ante omitted firm characteristics.

The estimated coefficients in Table 6 are economically meaningful. These results suggest that

Table 7: AI Pricing and Heterogeneous Firm Performance: Long-differences

	Δ Log Sales		Δ Log Employment		Δ Log Assets	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta APS_{j,[2010,2023]}$× Size Small	0.606	0.235	0.606	0.235	0.606	0.235
	(0.516)	(0.479)	(0.516)	(0.479)	(0.516)	(0.479)
$\Delta APS_{j,[2010,2023]}$× Size Medium	2.008***	1.676***	2.008***	1.676***	2.008***	1.676***
	(0.605)	(0.534)	(0.605)	(0.534)	(0.605)	(0.534)
$\Delta APS_{j,[2010,2023]}$× Size Large	2.919***	2.305***	2.919***	2.305***	2.919***	2.305***
	(0.875)	(0.787)	(0.875)	(0.787)	(0.875)	(0.787)
Controls	N	Y	N	Y	N	Y
Industry×Szie Group FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
N	4005	3583	4005	3583	4005	3583
adj. R^2	0.135	0.221	0.135	0.221	0.135	0.221

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We do not include 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

adopting AI-powered pricing is positively associated with firm growth. However, it is important to note that the correct interpretation of our results is not that the adoption of AI pricing, without any other adjustments, will directly drive additional sales growth. Instead, the main mechanism should be that AI pricing appears to stimulate firm growth through faster and more accurate demand estimations, so firms could quickly and more accurately adjust their prices to maintain a higher markup.

Building an AI pricing team could be very costly initially, but once adopted, firms with more products and operating in more sub-markets could benefit more. Table 7 shows that the benefits from AI pricing adoption are not evenly distributed across the distribution of initial firm sizes measured by employment in 2010. The table shows that the positive relations between the adoption of AI pricing and firm growth are stronger for larger firms. The correlations between AI pricing adoption and firm growth are insignificantly different from zero for the bottom one-third of the firms. This is consistent with the findings that big data and AI technologies have scale-economy effects that favor large firms (Farboodi et al., 2019; Babina et al., 2024). The results suggest that, with fixed costs of acquiring big data and setting up AI pricing teams, larger firms are more likely to benefit from AI pricing, which enables them to adjust prices based on faster and more accurate estimates of changes market conditions.

4.2 Evidence from High-Frequency Monetary Policy Shocks

Finally, we leverage the transmission of high-frequency identified monetary policy shocks in the 30-minute window of FOMC announcements on firm-level daily stock returns to test the causal evidence of AI pricing adoption on firm performance. The identification is that firms' AI pricing adoption is predetermined upon the 30-minute window of FOMC announcements; therefore, differences in the responses of firm-level daily stock returns that are conditional on AI pricing adoption reflect how the firms' market value depends on AI pricing adoption.

4.2.1 Merge to CRSP, Monetary Policy Shocks, and FPA

To do so, we need to further merge our Lightcast-Compustat-Merged Data in Section 3.1 with CRSP Daily stock Return Data and a measure of high-frequency monetary policy shocks, which we follow Bauer and Swanson (2023)'s series starting from January 27, 2010, to December 11, 2019, in a total of 81 FOMC announcement events. We then extract the daily stock return of all our firm samples in Section 3.1 on the corresponding FOMC announcement dates.

To interpret the effects of monetary shocks more intuitively, we standardize the raw monetary shocks by flipping the sign and dividing by 25bps. We denote the adjusted monetary shock at event date e as MP_e. So, one unit change in the variable MP_e would be one standard unexpected FOMC operation. Finally, we also include the industry-level frequency of price adjustment measure (FPA_s) for industry s to compare to our lagged quarterly AI pricing share measure ($APS_{j,t-1}$) for firm j. Our industry-level frequency of price adjustments measure is from Pasten, Schoenle, and Weber (2020), which was originally calculated from micro PPI data in the Bureau of Labor Statistics. FPA_s is one over the average duration of prices within industry s. Table 8 summarizes the newly merged variables of monetary shocks, frequency of price adjustments, daily stock returns, and other firm-level variables.

4.2.2 Regression Specifications and Results

Using the monetary policy shock series, we apply the following event-level (e) empirical specification to assess whether AI pricing adoption leads to differential responses of stock returns,

$$\begin{aligned} R_{j,e} = \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times X_{j,t-1} + \beta_3 X_{j,t-1} \\ + \beta_4 Z_{j,t-1} + \beta_5 MP_e \times Z_{j,t-1} + \gamma_j + \gamma_e + \epsilon_{je}, \end{aligned} \tag{3}$$

where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e is our monetary shocks, $X_{j,t-1}$ denotes the variables of interest (demeaned if are continuous), including firm-level

Table 8: Summary of Monetary Shocks, FPA, Stock Returns, and Other Variables

Variables	Obs.	Mean	Std.Dev.	Min	Max
MP_e	81	-0.0207	0.1141	-0.2812	0.3244
FPA_s	134	0.1420	0.1310	0.0334	0.7613
Stock Returns (%)	184996	0.0823	3.0111	-65	224
$APS_{j,t-1}$	107925	0.0044	0.0482	0	1
$\mathbb{1}^{AP}_{j,t-1}$	185122	0.4487	0.4974	0	1
Share of AI	177019	0.0041	0.0288	0	1
Share of Pricing	177019	0.0126	0.0539	0	1
Log Sales	174603	5.3192	2.0323	-7	12
Log Age	167715	3.0140	0.8641	0	5
Log TFP	156558	0.0508	0.8764	-8	6
Log Tobin's Q	176692	0.5502	0.5630	-1	4
Cash/Asset	176835	0.1833	0.2197	0	1
Log Markup	174071	0.6481	0.8841	-11	9

Notes: This table summarizes our Lightcast Job Posting Data merged with Compustat Quarterly, monetary policy shocks (MP_e) from Bauer and Swanson (2023), frequency of price adjustments (FPA_s) from Pasten, Schoenle, and Weber (2020), and daily stock returns from CRSP from 2010Q1 to 2019Q4. The balance sheet variables are winsorized at the top and bottom 1%. The two measures of AI pricing adoption are constructed as follows. First, we construct a dummy indicator of AI pricing adopter $\mathbb{1}^{AP}_{j,t}$ which equals one if firm j posted at least one AI pricing job since the beginning of our data sample until time t. Second, we construct an intensity indicator of AI pricing job posting as a share of pricing job posting $APS_{j,t}$, which divides the above total number indicator of AI pricing job posting numbers $APN_{j,t}$ by the total number indicator of pricing job posting numbers. We use cumulative rather than periodic measures to avoid noises caused by large short-run fluctuations in job postings.

lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$, firm-level lagged AI pricing adoption share $APS_{j,t-1}$, and industry-level frequency of price adjustment FPA_s, where t denotes a quarter and s denotes a NAICS 6-digit industry. We also include the same group of firm-level controls as in the long-differences regressions, including (1) lagged firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash/asset); and (2) lagged firm-level share of AI workers and share of pricing workers which are orthogonal to the firm-level lagged AI pricing adoption share $APS_{j,t-1}$. We also include lagged markup as an additional control. Finally, we include firm fixed effects and event fixed effects. Our identification operates through changes in the discounted value of profits from changes in future demand and costs, which are immediately reflected in stock returns following the monetary policy surprises.

Table 9 presents the result of our regression specification (3), where $X_{j,t-1}$ includes the firm-level lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$ and industry-level frequency of price adjustment FPA_s. Different columns vary in specifications by turning firm-level controls and firm fixed effects on and off. We do not include event fixed effects here, so we can see the average effects

Table 9: Stock Return Response to Monetary Shocks: AI Pricing Dummy

	(1)	(2)	(3)	(4)	(5)	(6)
$MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{0}$	2.444^{***}	2.430^{***}	2.471^{***}	2.825^{***}	2.897^{***}	2.943^{***}
	(0.079)	(0.079)	(0.079)	(0.189)	(0.171)	(0.172)
$MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$	2.956^{***}	2.965^{***}	3.079^{***}	3.302^{***}	3.174^{***}	3.350^{***}
	(0.094)	(0.107)	(0.109)	(0.210)	(0.242)	(0.246)
$\mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$	0.038^{***}	0.024	-0.047^{*}	0.025	0.033	-0.030
	(0.014)	(0.016)	(0.025)	(0.032)	(0.037)	(0.059)
$MP_e \times FPA_s$				0.527^{***}	0.525^{***}	0.524^{***}
				(0.140)	(0.128)	(0.128)
FPA_s				0.040^{**}	0.018	
				(0.016)	(0.016)	
Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y
N	184996	149043	149043	49418	36840	36840
adj. R^2	0.010	0.011	-0.010	0.010	0.013	-0.011

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Empirical specification: $R_{j,e} = \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times X_{j,t-1} + \beta_3 X_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 MP_e \times Z_{j,t-1} + \gamma_j + \gamma_e + \epsilon_{je}$, where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e is our monetary shocks, $X_{j,t-1}$ denotes the variables of interest (demeaned if are continuous), including firm-level lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$, firm-level lagged AI pricing adoption share $APS_{j,t-1}$, and industry-level frequency of price adjustment FPA_s, where t denotes a quarter and s denotes a NAICS 6-digit industry. We also include the same group of firm-level controls as in the long-differences regressions, including (1) lagged firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash/asset); and (2) lagged firm-level share of AI workers and share of pricing workers which we orthogonal to the firm-level lagged AI pricing adoption share $APS_{j,t-1}$. We also include lagged markup as an additional control. Finally, we include firm fixed effect and event fixed effect. Our identification operates through changes in the discounted value of profits from changes in future demand and costs that are immediately incorporated in stock returns following the monetary policy surprises.

of monetary surprises. First, all columns show that monetary expansions cause positive stock returns at the firm level. The point estimate is economically large and statistically significant at the 1% level: a hypothetical policy surprise of 25 bps leads to an increase in a return of about 2.5 to 3.0 percentage points for firms that non-adopters of AI pricing ($\mathbb{1}^{AP}_{j,t-1} = \mathbf{0}$). Second, for firms that adopted AI pricing ($\mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$), the effects of the same policy surprise increase to about 3.0 to 3.4 percentage points. The gap between the two is about 0.5 percentage points and is quite robust and significant across different specifications. Third, the gap between the two is quantitatively comparable to the marginal effects of a higher frequency of price adjustment.

Table 10 presents the result of our baseline regression specification (3), where $X_{j,t-1}$ are the firm-level lagged AI pricing adoption share $APS_{j,t-1}$ and industry-level frequency of price adjustment FPA_s. We demeaned both $APS_{j,t-1}$ and FPA_s, so now we could interpret the estimated coefficient on MP_e as the average effect. We also standardize FPA_s by dividing by its standard deviation. Still, we do not standardize $APS_{j,t-1}$ since it has direct economic meanings of the ratio

Table 10: Stock Return Response to Monetary Shocks: AI pricing Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP_e	2.394***	2.432***	2.488***		2.805***	2.898***	2.942***	
	(0.067)	(0.070)	(0.070)		(0.148)	(0.152)	(0.152)	
$MP_e \times APS_{j,t-1}$	3.930***	3.656***	3.546**	4.231***	6.680**	6.252**	5.810*	5.743**
	(1.360)	(1.398)	(1.410)	(1.275)	(2.990)	(2.948)	(3.021)	(2.744)
$APS_{j,t-1}$	0.084	-0.010	0.055	0.223	0.271	0.404	0.577	0.517
	(0.164)	(0.173)	(0.440)	(0.397)	(0.331)	(0.341)	(0.692)	(0.629)
$MP_e \times FPA_s$					0.494***	0.497***	0.510***	0.564***
					(0.127)	(0.129)	(0.129)	(0.117)
FPA_s					0.029*	0.025		
					(0.015)	(0.019)		
Controls	N	Y	Y	Y	N	Y	Y	Y
Firm FE	N	N	Y	Y	N	N	Y	Y
Event FE	N	N	N	Y	N	N	N	Y
N	112844	104855	104855	104855	28779	26790	26790	26790
adj. R^2	0.011	0.012	-0.008	0.176	0.013	0.015	-0.006	0.170

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Empirical specification: $R_{j,e} = \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times X_{j,t-1} + \beta_3 X_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 MP_e \times Z_{j,t-1} + \gamma_j + \gamma_e + \epsilon_{je}$, where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e is our monetary shocks, $X_{j,t-1}$ denotes the variables of interest (demeaned if are continuous), including firm-level lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$, firm-level lagged AI pricing adoption share $APS_{j,t-1}$, and industry-level frequency of price adjustment FPA_s, where t denotes a quarter and s denotes a NAICS 6-digit industry. We also include the same group of firm-level controls as in the long-differences regressions, including (1) lagged firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash/asset); and (2) lagged firm-level share of AI workers and share of pricing workers which we orthogonal to the firm-level lagged AI pricing adoption share $APS_{j,t-1}$. We also include lagged markup as an additional control. Finally, we include firm fixed effect and event fixed effect. Our identification operates through changes in the discounted value of profits from changes in future demand and costs that are immediately incorporated in stock returns following the monetary policy surprises.

of AI pricing workers over the total pricing team. Again, from all columns except 4 and 8, which control for event fixed effects, we find that a 25 bps unexpected monetary expansion causes stock return to rise by about 2.5 to 3.0 percentage points, consistent with our findings in Table 9. Firms with a higher share of AI pricing significantly benefit more from this monetary expansion. Focusing on column 8, the interpretation is that from a firm that does not adopt AI pricing at all to a firm with about 16% share of AI pricing (i.e., Amazon), the stock return responses would be topped up by an additional one percentage point. This magnitude is economically significant and meaningful, meaning Amazon would be about 35% more responsive to such a monetary expansion. By comparing this magnitude to the effects of monetary shocks interacting with the frequency of price adjustment, an AI pricing adoption share $APS_{j,t-1}$ = 10% is on per with increasing the frequency of price adjustment by one standard deviation. Finally, in Table C11, we include interactions of monetary policy shocks with all the controls to see if other predetermined

Table 11: Stock Return Response to Monetary Shocks: Interaction with Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MP_e \times APS_{j,t-1}$	4.881*	5.354**	5.391**	5.377**	5.794**	5.362**	5.725**	5.460**	5.200*
	(2.704)	(2.694)	(2.695)	(2.695)	(2.695)	(2.694)	(2.699)	(2.694)	(2.715)
$MP_e \times FPA_s$	0.486***	0.470***	0.491***	0.469***	0.426***	0.430***	0.443***	0.406***	0.409***
	(0.116)	(0.116)	(0.122)	(0.116)	(0.117)	(0.118)	(0.118)	(0.120)	(0.127)
$MP_e \times$ Share of AI	10.855**								13.588***
	(4.608)								(4.702)
$MP_e \times$ Share of Pricing		-2.934							-2.762
		(2.108)							(2.113)
$MP_e \times$ Log Sales			-0.040						0.039
			(0.083)						(0.107)
$MP_e \times$ Log Age				-0.133					-0.159
				(0.170)					(0.182)
$MP_e \times$ Log TFP					-0.628***				-0.690***
					(0.164)				(0.251)
$MP_e \times$ Log Tobin's Q						-0.598**			-0.239
						(0.253)			(0.311)
$MP_e \times$ Cash/Asset							-1.351*		-0.889
							(0.775)		(1.016)
$MP_e \times$ Log Markup								-0.556**	0.262
								(0.235)	(0.345)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	24432	24432	24432	24432	24432	24432	24432	24432	24432
adj. R^2	0.175	0.175	0.175	0.175	0.176	0.175	0.175	0.175	0.176

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Empirical specification: $R_{j,e} = \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times X_{j,t-1} + \beta_3 X_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 MP_e \times Z_{j,t-1} + \gamma_j + \gamma_e + \epsilon_{je}$, where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e is our monetary shocks, $X_{j,t-1}$ denotes the variables of interest (demeaned if are continuous), including firm-level lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$, firm-level lagged AI pricing adoption share $APS_{j,t-1}$, and industry-level frequency of price adjustment FPA_s, where t denotes a quarter and s denotes a NAICS 6-digit industry. We also include the same group of firm-level controls as in the long-differences regressions, including (1) lagged firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash/asset); and (2) lagged firm-level share of AI workers and share of pricing workers which we orthogonal to the firm-level lagged AI pricing adoption share $APS_{j,t-1}$. We also include lagged markup as an additional control. Finally, we include firm fixed effect and event fixed effect. Our identification operates through changes in the discounted value of profits from changes in future demand and costs that are immediately incorporated in stock returns following the monetary policy surprises.

firm characteristics cause the main findings. Including these interactions reduces the significance of our main result, but it is still at about 95% confidence interval.

4.3 Robustness Checks

We check various robustness of the long-differences results in Online Appendix C.1, including across industry heterogeneity (C.1.1), excluding largest firms (C.1.2), and controlling for changes in AI share and pricing share (C.1.3). We also check various robustness of the monetary policy shock results in Online Appendix C.2, including excluding financial and utility firms (C.2.1) and excluding IT firms (C.2.2). We find the firm performance patterns of AI pricing are generally consistent with our main results.

5 A Stylized Model of AI pricing Adoption

To understand the economic mechanism, we introduce a simple stylized model of AI pricing adoption focusing on the essential role of AI in reducing information friction. In the model, firms face their demand, a high-dimensional function of market characteristics, so they use pricing labor and algorithmic computing to learn about the demand function for their goods. Learning about more aspects of the demand function allows firms to price discriminate more effectively.

To make the model simple and tractable, we abstract away two extended dimensions of AI pricing: dynamics and competition. Both come naturally with the reduction of information friction in pricing decisions. First, firm decisions are entirely static, and all intertemporal variations are only driven by the trend of changes in the price of computing. Second, the model has no competition; all firms are monopolists. This abstracts from the interaction between algorithms and competition explored in Klein (2021), Brown and MacKay (2023), and elsewhere. Rather, we study another mechanism: how capital-labor complementarity incentivizes firms to adopt AI pricing over time and how it affects their size and profitability.

The model first explains four main patterns documented in the data except for the across-industry variations: the adoption rate of AI pricing and the AI share of pricing labor both rise over time, while the AI pricing is correlated with both revenue and markups in the cross-section. We also use the model to explore the effects of aggregate demand shifters.

5.1 General Environment and Firm's Problem

General Environment We first consider the pricing problem of a monopolist firm. The firm sells a single good, which it produces at constant marginal cost κ. It sells this good in a continuum of submarkets indexed by j. The continuum of submarkets has measure μ, which stands for unmodeled factors affecting the firm's size. Each submarket might represent individual buyers, consumer groups, regions, platforms, or other market disaggregation. We refer to submarkets as *individuals* for concreteness.

The firm chooses the price p_j offered to individual j. Individuals have a j-specific quantity demand function $d_j(p_j)$. For tractability, we suppose that the demand functions are linear:

$$d_j(p_j) = z_j - \eta p_j \tag{4}$$

where the slope η is common for all individuals, but the intercept z_j varies. The information friction firms face is that they do not know z_j.

Pricing Problem with Uncertain Demand We then describe how firms price conditional on having some information about z_j. We let Ω denote a firm's information set. The firm's objective is to maximize profits by choosing a price p_j for each individual. The profit π_j earned from a given individual is

$$\pi_j(p_j) = (p_j - \kappa)d_j(p_j)$$

therefore, the firm's conditional objective is

$$\max_{p_j \ j \in \mathcal{J}} \mathbb{E}\left[\int_{j \in \mathcal{J}} (p_j - \kappa)d_j(p_j)dj \, |\Omega\right] \tag{5}$$

Lemma 1 *Facing linear demand function (4), the firm's optimal price is*

$$p_j = \frac{\mathbb{E}\left[z_j|\Omega\right]}{2\eta} + \frac{\kappa}{2}$$

Proof: Appendix D.1.1

Usually, monopolists face linear demand and set prices as a linear combination of marginal and intercept costs. The same is true in this model of uncertain demand, except the price depends on the firm's expectation of the intercept.

5.2 Information Acquisition and Optimal Pricing

Information Structure The individual-specific demand term z_j is determined by a large number of different factors, $\{x_{j,n}\}_{n=0}^{\infty}$. We abstract from data acquisition challenges and assume that the factors are all observed by the firm. However, the firm does not know the *function* through which these factors affect demand. Specifically, demand is given by

$$z_j = \overline{z} + b_0 x_{j,0} + b_1 x_{j,1} + b_2 x_{j,2} + \ldots$$

and the coefficients $\{b_n\}_{n=0}^{\infty}$ are unknown *ex ante*. $\overline{z}$ is an unconditional mean which *is* known. Firms will use resources to learn about these coefficients in order to nowcast z_j.[5] Firm will make information acquisition decisions before observing the data $\{x_{j,n}\}_{n=0}^{\infty}$. Therefore, they will need some idea of how the data will be distributed. We assume that $x_{j,n}$ are Gaussian and uncorrelated. Given the orthogonality assumption, these factors can be interpreted as the principal components of the demand-relevant data.

For the purposes of using calculus, it is convenient to extend the factor indexing to the real line. Thus, we write z_j as an integral rather than a sum:

$$z_j = \overline{z} + \int_0^{\infty} b(n)x_j(n)dn$$

where $\overline{z}$ denotes the unconditional average $\overline{z} = \mathbb{E}[z_j]$; we assume $\overline{z} > \eta\kappa$ so that firms are willing to produce.[6] We scale the factors to have unit variance and sign the factors so that $b(n)$ is positive. The factors are then ordered in descending importance, so $b(n)$ decreases. Thus, factor $x_j(0)$ is most important for nowcasting z_j, factor $x_j(1)$ is less important than $x_j(0)$ but more important than $x_j(2)$, and so forth. All else being equal, firms would prefer to know low-indexed factors to high-indexed factors.

Suppose firms observe factors $x(n)$ for all $n \leq N$. Then, we write the firm's nowcast as

$$\mathbb{E}_N z_j \equiv \mathbb{E}[z_j|\Omega] = \overline{z} + \int_0^{N} b(n)x_j(n)dn$$

Additionally, the standard normal scaling and orthogonality assumption imply that the unconditional forecast variance is

$$\mathbb{V}\left[\mathbb{E}_N z_j\right] = \int_0^{N} \mathbb{E}\left[b(n)^2\right] dn$$

This unconditional variance is an increasing function of N. From it, we define the function $R(N)$:

$$R(N) \equiv \frac{\mathbb{V}\left[\mathbb{E}_N z_j\right]}{\nu}$$

where $\nu \equiv \mathbb{V}\left[z_j\right]$. The function $R(N)$ captures the share of the variance of z_j that is nowcastable by a firm observing N factors (analogous to an R^2 statistic). $R(N)$ is both increasing and differ-

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[5] Note that the coefficients are common across individuals j; they encode the general, high-dimensional demand function estimated by firms. There may also be some unknowable j-specific residual; this would complicate our notation but not our analysis.

[6] It is possible that for some markets, $z_j < \eta\kappa$. We assume that firms commit to supplying each market for tractability before observing demand factors and setting prices by Lemma 1. Thus, they make profits in expectation, but possibly not ex-post in all markets.

entiable.

Information Acquisition Firms use real inputs in order to observe the function coefficients $\{b_n\}_{n=0}^{\infty}$. They can select which coefficients to observe, so they will choose the most valuable for nowcasting, i.e., those with the lowest indices. Thus, their selection can be summarized by N, the maximum index they choose to observe.

Firms have a production function for observing indices. The number of indices they can observe is given by

$$N = F(L_a, L_b, C)$$

where F is some increasing function of three inputs. The first two inputs are types of labor: basic pricing labor L_b and AI pricing labor L_a. These types are substitutes but draw from the same labor pool at wage w. However, AI pricing labor can use algorithmic computing C as a complementary input. Algorithmic computing, which includes processing costs, software, and IT support, is purchased at q. In order to model the discrete adoption decision, we also assume that firms must pay the fixed cost χ if they choose to use any AI pricing.

Firm's Optimal Pricing To characterize the firm's behavior, it is first useful to derive the unconditional expectation of the firm's profit

Lemma 2 *The firm's unconditional expected profit is*

$$\mathbb{E}\left[\int_{j\in\mathcal{J}} \pi_j(p_j)dj\right] = \mu\Phi\nu R(N)$$

where

$$\Phi \equiv \frac{(\bar{z} - \eta\kappa)^2}{4\eta} \tag{6}$$

Proof: Appendix D.1.2

Lemma 2 demonstrates that profits are linearly increasing in the nowcastable share $R(N)$ of the variance. This is because firms try to price discriminate but make errors when they do not precisely know the demand functions that they face. When firms choose a larger $R(N)$, they have less uncertainty over demand, allowing them to price discriminate more effectively and raising profits.

Before observation, firms solve the following *ex-ante* profit-maximization problem, using the Lemma 2 expression for the expected profit:

$$\max_{N,L_a,L_b,C} \mu\Phi\nu R(N) - w(L_a + L_b) - qC - \chi\mathbb{1}(L_a C > 0)$$

$$s.t.\ N = F(L_a, L_b, C)$$

where $\mathbb{1}(L_a C > 0)$ is an indicator function that takes value 1 if and only if both AI pricing inputs L_a and C are strictly positive. The first order condition for basic pricing labor is

$$\mu \Phi \nu R'(N) F_b(L_a, L_b, C) = w \tag{7}$$

If firms do not adopt AI pricing, then $L_a = 0 = C$. But if they do adopt AI pricing and choose $L_a > 0 < C$, then their first order conditions for these inputs are

$$\mu \Phi \nu R'(N) F_a(L_a, L_b, C) = w \tag{8}$$

$$\mu \Phi \nu R'(N) F_c(L_a, L_b, C) = q \tag{9}$$

where F_a, F_b, and F_c denote the partial derivatives with respect to the first, second, and third arguments of $F(L_a, L_b, C)$. If AI pricing is adopted, then with some simplification, we learn that the marginal product of labor types must be equal:

$$F_a(L_a, L_b, C) = F_b(L_a, L_b, C) \tag{10}$$

and the marginal rate of transformation between labor and computing is given by the ratio of the wage to the computing price:

$$\frac{F_a(L_a, L_b, C)}{F_c(L_a, L_b, C)} = \frac{w}{q} \tag{11}$$

5.3 Functional Forms and Aggregation

Functional Forms In order to explore the model, we select some functional forms. First, we assume that the variance of components $b(n)$ is constant until all variance is explained:

$$\mathbb{E}\left[b(n)^2\right] = \begin{cases} \rho & n \leq \frac{\nu}{\rho} \\ 0 & n > \frac{\nu}{\rho} \end{cases}$$

where ν denotes the unconditional variance $\mathbb{V}[z_j] = \nu R(\frac{\nu}{\rho})$ since the function $R(N)$ is given by

$$R(N) = \frac{\int_0^N \mathbb{E}\left[b(n)^2\right] dn}{\nu} = \min(\frac{\rho}{\nu} N, 1)$$

Second, we assume that the production function for observing N function components are

$$F(L_a, L_b, C) = L_b^{\beta} + (AL_a)^{\alpha} C^{\gamma} \tag{12}$$

We assume $\beta \in (0,1)$, $\alpha > 0$, $\gamma > 0$ and $\alpha + \gamma < 1$. A is labor-augmenting productivity that weights the relative contribution of the two components. This specific production function is motivated by the idea that computing is complementary to AI pricing workers relative to traditional pricing workers.

One consequence of the semi-separable production function (12) is that the adoption decision is independent of the choice of basic pricing labor L_b (so long as $\rho N < \nu$). If firms adopt AI pricing, the usual first-order conditions from their optimal pricing decisions apply, but firms only choose nonzero L_a and C if the value of the output from the AI technology $(AL_a)^{\alpha} C^{\gamma}$ is at least as large as the associated costs. This condition is

$$\mu \Phi (AL_a)^{\alpha} C^{\gamma} \geq wL_a + qC + \chi \tag{13}$$

To understand the factors that lead firms to adopt any AI pricing, define the threshold function $\underline{\mu}(q)$ which measures the minimum value of μ such that firms are willing to use AI pricing, i.e. the minimum μ such that condition (13) holds. We keep wages and productivity fixed, so this threshold is only a function of the computing price q. We assume that $1 > (\alpha + \gamma)\alpha^{-\gamma}\gamma^{\gamma}$ which ensures that $\underline{\mu}(q)$ can be positive; if the returns to scale in AI pricing were too small, then it could be that no one would be willing to use the technology.

Lemma 3 *The minimum market size μ such that firms are willing to use AI pricing $\underline{\mu}(q)$ is increasing in q.*

Proof: Appendix D.1.3

Lemma 3 tells us when firms will choose to adopt AI pricing at all: if a firm has market size $\mu \geq \underline{\mu}(q)$, then the firm is willing to use the technology. Why is $\underline{\mu}(q)$ an increasing function? Consider the condition (13); a larger market μ increases the incentive to use AI pricing, while a larger q increases the cost of doing so. If the computing cost q decreases, then firms with smaller market sizes μ are able to satisfy the condition and will adopt AI.

Aggregation The stylized model describes a static decision of a single monopolist. However, our empirical results describe AI pricing labor over time and in the cross-section. To map these patterns to the model, we consider time variation to be driven solely by changes in the computing price q. We also consider cross-section variation driven by heterogeneity in firms' market size μ.

Specifically, we assume that μ is distributed with CDF $H(\mu)$.

Let the function $s_{AI}(\mu, q)$ denote a firm's choice of AI share of pricing labor $\frac{L_a}{L_a+L_b}$ as a function of its market size μ and computing price q. Then the *economy-wide AI share* $S_{AI}(q)$ is given by

$$S_{AI}(q) = \int_{\mu} s_{AI}(\mu, q) dH(\mu)$$

Firms adopt AI pricing if $\overline{\chi}(q, \mu) \geq \chi$. Let $\underline{\mu}(q)$ denote the threshhold value of μ such that $\overline{\chi}(q, \mu) = \chi$. Firms with $\mu \geq \underline{\mu}(q)$ are willing to adopt AI pricing, so the economy-wide adopting fraction of firms is given by

$$\mathcal{A}_{AI}(q) = 1 - H(\underline{\mu}(q))$$

In the quantitative results presented in Figure 4, we let market size μ be distributed Pareto with minimum μ_{min} and shape parameter ξ. In this case, the DDF is given by

$$\text{[Pareto:]} \qquad 1 - H(\mu) = \left(\frac{\mu_{min}}{\mu}\right)^{\xi}$$

5.4 Stylized Facts vs Model Predictions

With the functional forms and the aggregation, we can now compare the model's predictions to the empirical patterns documented in Sections 3 and 4. The model describes the following four propositions that match the stylized facts on the rise of AI pricing:

1. As the price of computing q falls, the adoption rate of AI pricing increases (Proposition 1)
2. As the price of computing q falls, the AI share of pricing labor increases (Proposition 2)
3. Larger firms choose a greater AI share of pricing labor (Proposition 3)
4. Firms choosing a greater AI share of pricing labor have higher markups (Proposition 4)

The remainder of this section proves these results. Throughout, we implicitly assume an *interior solution for factor observation*, i.e., $N < \frac{\nu}{\rho}$.

5.4.1 The Rise of AI Pricing in the Time Series

Proposition 1 ***Adoption Rate of AI Pricing:*** *The fraction of firms adopting AI pricing* $\mathcal{A}_{AI}(q)$ *increases when the computing price* q *decreases.*

Proof. Lemma 3 says that $\underline{\mu}(q)$ is increasing in q and the CDF $H(\mu)$ is necessarily an increasing function, so the fraction of adopting firms $\mathcal{A}_{AI}(q) = 1 - H(\underline{\mu}(q))$ must be decreasing in q. ■

Proposition 1 holds because the computing price q increases the cost of AI. So when q decreases, more firms are willing to pay the costs and adopt the technology.

For the next stylized fact on AI pricing labor share, Lemma 4 provides an intermediate result.

Lemma 4 *Conditional on adopting AI pricing, a firm's AI share of pricing labor* $\frac{L_a}{L_a+L_b}$ *increases when the computing price* q *decreases.*

Proof: Appendix D.1.4

Lemma 4 intuitively says that as the inputs to AI pricing become cheaper, firms will do more AI pricing relative to basic pricing, and will hire accordingly. Proposition 2 follows immediately from the last two results.

Proposition 2 ***The AI Share of Pricing Labor:*** *The economy-wide AI share of pricing labor* $S_{AI}(q)$ *increases when the computing price* q *decreases.*

Proof. Proposition 1 implies that the fraction of firms $\mathcal{A}_{AI}(q)$ choosing non-zero AI must be decreasing in q. Conditional on adopting AI pricing, Lemma 4 says that a firm's AI share $\frac{L_a}{L_a+L_b}$ is decreasing in q. Given these two relationships, it must be that the economy-wide AI share $\mathcal{S}_{AI}(q) = \int_\mu s_{AI}(\mu, q) dH(\mu)$ is decreasing in q. ■

5.4.2 AI Share of Pricing Labor, Revenue, and Markup in the Cross-Section

Firms vary by market size μ. Firms selling in more submarkets have greater incentives to learn their customers' demand functions. Proposition 3 says that larger firms will hire a greater AI share of pricing labor if $\beta < \alpha + \gamma$ holds. This condition implies that AI pricing has a returns-to-scale advantage over basic pricing, due to its complementarity with algorithmic computing.

Several intermediate lemmas are first necessary to prove this result.

Lemma 5 *Conditional on adopting AI pricing, a firm's AI share of pricing labor* $\frac{L_a}{L_a+L_b}$ *is strictly increasing in its market size* μ *if and only if* $\beta < \alpha + \gamma$.

Proof: Appendix D.1.5

μ is a measure of firm size, but one that does map directly to accounting data. The next Lemmas are used to connect μ to firm revenues.

Lemma 6 *Conditional on adopting AI pricing, the observation N chosen by a firm is increasing in its market size μ and decreasing in the computing price q.*

Proof: Appendix D.1.6

Lemma 7 *Conditional on adopting AI pricing, a firm's revenue is increasing in its market size μ, decreasing in the computing price q, and given by*

$$y = \mu \frac{\nu R(N) + \overline{z}^2 - \eta^2 \kappa^2}{4\eta} \tag{14}$$

Proof: Appendix D.1.7

Proposition 3 ***The AI Share of Pricing Labor and Revenue in the Cross-Section:*** *Given a computing price q, a firm's AI share of pricing labor $\frac{L_a}{L_a+L_b}$ is weakly increasing in its revenue y if $\beta < \alpha + \gamma$.*

Proof. For firms with $\mu < \underline{\mu}(q)$, revenue is increasing in μ (Lemma 7) but $L_a = 0$ so the AI share of pricing labor is not. For firms with $\mu \geq \underline{\mu}(q)$, revenue is increasing in μ (Lemma 7) as is the AI share, $\frac{L_a}{L_a+L_b}$, if $\beta < \alpha + \gamma$ (Lemma 5). Therefore, $\frac{L_a}{L_a+L_b}$ is weakly increasing in revenue y. ■

As in the last section, firms operating in more markets have greater incentives to learn the demand function by hiring pricing inputs. This makes larger firms more effective price discriminators, which allows them to charge higher markups. Because larger firms hire a greater AI share of pricing labor in order to take advantage of the returns to scale afforded by the computing input, we observe a positive correlation between the AI share and markups in the cross-section.

Lemma 8 connects markups to market size, and then Proposition 4 proves the stylized fact.

Lemma 8 *Conditional on adopting AI pricing, a firm's average markup $m = \frac{Revenue}{Cost} - 1$ is increasing in its market size μ and decreasing in the computing price q.*

Proof: Appendix D.1.8

Proposition 4 ***The AI Share of Pricing Labor and Markups in the Cross-Section:*** *Given a computing price q, a firm's AI share of pricing labor $\frac{L_a}{L_a+L_b}$ is weakly increasing in its markup m if $\beta < \alpha + \gamma$.*

Proof. For firms with $\mu < \underline{\mu}(q)$, the markup is increasing in μ (Lemma 8) but $L_a = 0$ so the AI share of pricing labor is not. For firms with $\mu \geq \underline{\mu}(q)$, the markup is increasing in μ (Lemma 8) as is the AI share, $\frac{L_a}{L_a+L_b}$, if $\beta < \alpha + \gamma$ (Lemma 5). Therefore, $\frac{L_a}{L_a+L_b}$ is weakly increasing in the markup m. ■

5.4.3 Model Predictions Comparing with the Data

These results demonstrate that the stylized facts hold in the model. Over time, as the price of computing falls, firms are more likely to adopt AI pricing (Proposition 1) firms employ more AI pricing labor as a share of total pricing labor (Proposition 2). If the basic pricing technology does not have a returns-to-scale advantage (i.e. $\beta < \alpha + \gamma$), then larger firms will also choose higher $\frac{L_a}{L_a+L_b}$ (Proposition 3) and earn greater markups (Proposition 4).

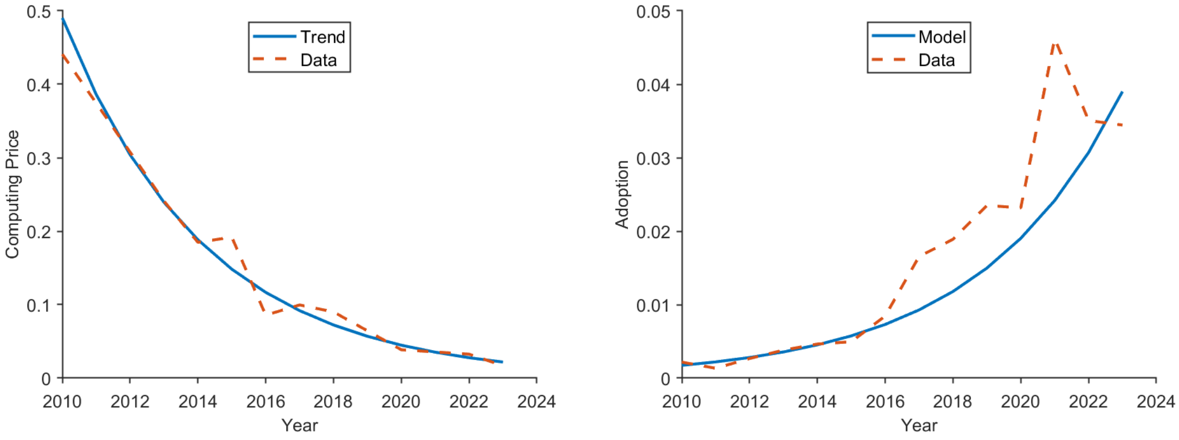
To demonstrate these results, we compute the model with an illustrative calibration. Broadly, the parameters are chosen to match the intertemporal and cross-sectional trends. We set $\beta = 0.75$, $\alpha = 0.6$, and $\gamma = 0.2$, so both technologies have decreasing returns, but AI pricing has a small-scale advantage. The difference $\alpha + \gamma - \beta$ roughly controls the growth rate of the AI share among firms that have adopted it. Several parameters control the level; we set $\Phi = 1$ and $\rho = 1$ as normalization and match the average level of the share by setting the productivity at $A = 0.18$. Market size is distributed Pareto; we set the shape parameter at $\xi = 5$ and the minimum at $\mu_{min} = 0.15$ to match the adoption growth rate and level.

Figure 4 demonstrates how these stylized facts manifest in the model. The Figure also plots the empirical counterparts; while the model is very stylized, there is enough flexibility in the parameterization to match the empirical patterns closely. Panel (a) plots the computing price q, which we calculate from GPU prices as described in Appendix D.2. The time series trend in the cost of computing is the model input that generates all of the time series variability of the endogenous variables. Panel (b) demonstrates that as the price q declines, a greater share of firms are willing to pay the fixed cost to adopt AI pricing; in the plotted results, market size μ is distributed Pareto across firms. When the computing price q declines, AI pricing also increases along the intensive margin because firms take advantage of the superior returns to scale; Panel (c) captures both margins by plotting the average AI share of pricing labor in the economy over time. Lastly, Panel (d) plots the cross-section of firms in a single year, with the computing price set to the 2023 value. Firms with small market sizes have little revenue and are unwilling to adopt AI pricing. Above the threshold, firms adopt and hire an even greater AI share of pricing labor as they get bigger.

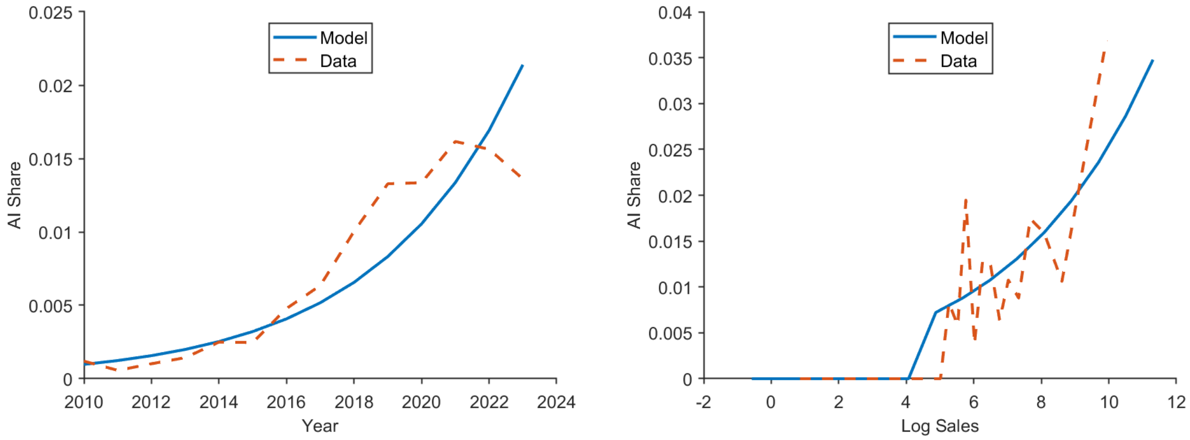
5.5 Effects of Demand Shifters

Thus far, we have considered how the supply side affects pricing decisions. While the simple model is designed to understand these supply-side factors – which drive the time-series and cross-sectional patterns documented in Sections 3 and 4 – the model also predicts how demand shocks interact with AI pricing, which links to the heterogeneous responses of stock returns to monetary

Figure 4: The Stylized Model vs Data



(a) AI Computing Cost (b) Share of Firms Using AI Pricing



(b) AI Share of Pricing Labor (d) AI Share of Pricing in the Cross-Section

Notes: The time-series data of AI computing cost is calculated from machine learning GPU costs, the time-series data of AI share of pricing labor is from Figure 1(a), the time-series and cross-section data of AI pricing adoption rate is also calculated from the Lightcast data, all described in Appendix D.2. The trend fitted in the model is an exponential function. The model takes the AI computing price trend as q each year. The figure plots outcomes from the stylized model parameterized with $\beta = 0.75$, $\alpha = 0.6$, $\gamma = 0.2$, $A = 0.18$, $\Phi = 1$, $\rho = 1$, $\xi = 5$, and $\mu_{min} = 0.15$, along with the counterparts from the data. In panels (b) and (c), $\mu = 1$ and q is taken as the computing cost trend. In panel (d), q is taken as the 2023 trend value, firms vary by μ, and the data are from the 2023 cross-section of firms divided into ventiles by log sales.

shocks conditional on AI pricing adoption and AI pricing share of labor in Section 4.2.

We model a shift in aggregate demand as a change in $\bar{z}$, the average demand intercept in each market. This change affects all firms symmetrically, so we consider $\bar{z}$ as representing aggregate factors determining consumers' willingness to consume. This should be properly done in general equilibrium in future work to make clear statements about macroeconomic outcomes. However, our simple partial equilibrium model still allows us to draw conclusions about the effects of demand. In particular, Proposition 5 reveals that firms will react heterogeneously to changes in demand in a way that is correlated with their adoption of AI pricing: specifically, firms that employ a greater AI share of pricing labor become relatively more profitable when demand increases.

But first, Lemma 9 describes how individual firms respond to demand changes:

Lemma 9 *For firms that adopt AI pricing, an increase in demand $\bar{z}$ ceteris paribus increases all of:*

1. *All pricing inputs L_a, L_b, C*
2. *The AI share of pricing labor $\frac{L_a}{L_a+L_b}$ if and only if $\beta < \alpha + \gamma$*
3. *Firm revenues*
4. *Gross profit*

Proof: Appendix D.1.9

The intuition of lemma 9 is as follows. If average demand $\bar{z}$ increases, there is a greater opportunity for price discrimination, so firms increase all pricing inputs to take advantage. Because AI pricing has a return-to-scale advantage, firms disproportionately increase AI pricing labor L_a relative to basic pricing labor L_b. Demand is higher, so the firm sells mechanically and earns greater gross profits; a component of this is mechanical because demand is higher, but another component is due to more effective price discrimination thanks to firms increasing their observation of demand factors N.

Proposition 5 ***The Effects of Demand shifters:*** *The response of gross profit π to an increase in $\bar{z}$ is greater for firms that do more AI pricing.*

Proof: Appendix D.1.10

Proposition 5 says that firms respond heterogeneously to changes in demand shifters. Firms vary by market size μ, and firms with larger market sizes are more sensitive to demand for two reasons. The first is mechanical: an overall increase in demand raises gross profits more for larger firms simply because they are exposed to more markets. But the second reason is specific to AI pricing: the marginal benefit of all pricing inputs is increasing in both market size μ and demand through Φ; moreover, market size and demand act as complements, so when one increases, it raises the marginal effect of the other. This is why the cross-partial derivative of factor observation $\frac{\partial^2 N(\bar{z},\mu)}{\partial\mu\partial\bar{z}}$ is positive. These results link to our evidence in Section 4.2.

6 Conclusion

We document evidence of the rise in AI pricing and study its implications for firm performance. We show that the importance of AI pricing has increased rapidly since 2010, and the increase in the usage of AI pricing has been widespread across industries. Our evidence suggests that larger and more productive firms are more likely to adopt AI pricing, and such adoption improves firm performance and increases the sensitivity of a firm's stock returns to monetary policy surprises. These empirical facts can be rationalized by a stylized model where a monopolist firm with incomplete information about the demand function invests in AI pricing to acquire information.

With continuing advances in computing technologies, especially the rapid decline in the cost of training and using AI, we expect the importance of AI pricing to grow further. To the extent that AI pricing can fundamentally change firms' pricing strategies, the trends in AI pricing have important implications for price stickiness, which could, in turn, change the traditional understanding of the transmission mechanism of monetary policy. An important subject for future research is to examine the quantitative impact of AI pricing on the frequencies and magnitudes of price adjustments using micro-level data. By establishing key stylized facts about AI pricing, our work takes an initial step toward a promising avenue for future research.

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Online Appendix to "The Rise of AI Pricing"
by Jonathan Adams, Min Fang, Zheng Liu, and Yajie Wang

Contents

A Supplements to The Rise of AI Pricing

A.1 Recent News Reports and Industry Reports on AI Pricing

We read through many news reports and industry reports to understand which features are most focused on the businesses that are actually using AI pricing or are considering adopting AI pricing. Below, we provide a few examples in case the audience is interested.

- Artificial intelligence may be a game changer for pricing, PwC, 2019
- Why AI transformations should start with pricing, Boston Consulting Group, 2021
- How companies use AI to set prices, Economist, 2022
- The art of pricing in the age of AI, EY, 2023
- Harnessing AI for dynamic pricing for your business, Forbes, 2024
- The rise of VaaS: How AI ss redefining SaaS pricing models, Crunchbase News, 2024
- AI-Enhanced pricing can boost revenue growth, Bain & Company, 2024
- Overcoming retail complexity with AI-Powered pricing, Boston Consulting Group, 2024
- Key pricing trends in 2024: AI conquers the mainstream, 7Learnings, 2024

A.2 Case Studies on Firms' AI pricing adoption

To illustrate the wide range of usages of AI pricing technologies by individual firms, we provide detailed summaries of the rough adoption patterns and uses of AI pricing within leading firms in several different industries, including online retailing, transportation, and finance. The timelines are roughly summarized for each firm from various newspaper and industrial reports resources, except Uber, which reports its progress on AI pricing adoptions.

A.2.1 Uber

Uber, founded in 2009, initially offers a premium black car service, allowing users to book rides through a smartphone app. The concept quickly gained popularity, and by 2011, Uber expanded to other U.S. cities. Its success came from the convenience of cashless transactions, dynamic pricing, and the ability to match riders with drivers. Over the years, Uber has faced regulatory challenges, driver protests, and competition but has continued to grow, offering new services like Uber X, Uber Eats, and autonomous vehicle projects. Despite controversies, Uber went public in 2019, cementing its role as a local transportation and food delivery leader in the gig economy. Given the nature of its real-time transportation and delivery operations, Uber sells to various customers in a dynamic environment, making it perfectly positioned to adopt AI pricing.

Uber AI pricing adoptions Uber is one of the most transparent firms on AI pricing changes since it either publishes reports on changes in pricing algorithms or allows developers and journalists to spot such changes in their developers' APIs. This could be because Uber needs to educate its customers to accept that AI pricing benefits them. Uber's adoption of AI-driven pricing systems evolves in several key stages:

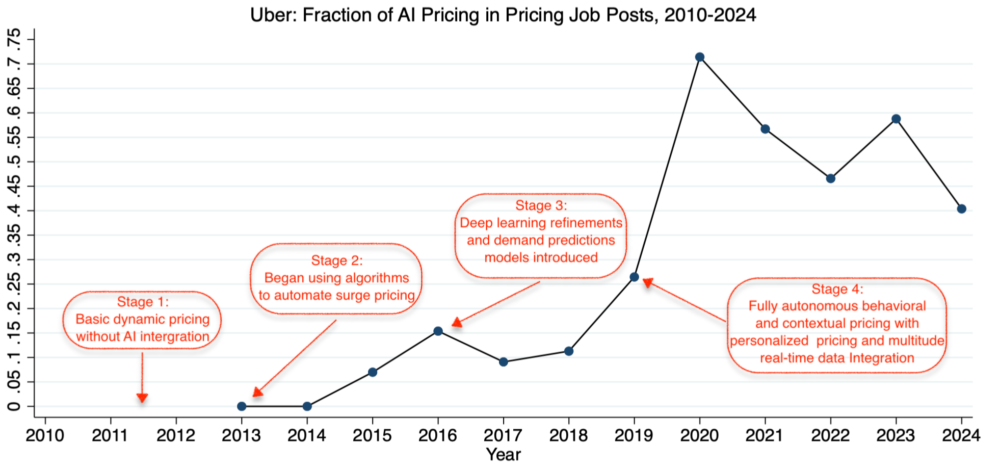
1. Early Dynamic Pricing (2010-2012): Uber implemented basic dynamic pricing to balance supply and demand early on. During periods of high demand (like holidays or inclement weather), prices would increase to incentivize more drivers to log on and meet demand. This early form of surge pricing was manually controlled and relatively simple, with limited data inputs. See www.uber.com/newsroom/take-a-walk-through-surge-pricing/.
2. Algorithmic Surge Pricing (2013-2015): By the end of 2012, Uber began using algorithms to automate surge pricing. These algorithms monitored real-time data from rides, locations, and drivers to adjust prices. The system became more efficient, using basic machine learning models to analyze historical data, predict rider demand, and calculate the optimal price to balance the market dynamically. AI models started incorporating geospatial data to predict specific regions where demand would spike. It could adjust city-wide pricing

for specific neighborhoods or events, making the system more granular and localized. See www.uber.com/en-GB/newsroom/nye-2012-surge.

3. Advanced AI and Machine Learning (2016-2018): (1). AI Refinement: Since 2016, Uber's AI pricing has become more sophisticated. It started using deep learning models to refine its dynamic pricing system, enabling it to process larger datasets in real-time. The AI learned to predict rider and driver behavior, factoring in variables like time of day, historical patterns, weather conditions, and major events. (2). Demand Prediction Models: These models allowed Uber to forecast demand spikes before they happened, adjusting prices proactively rather than reactively. For example, the system could anticipate demand in the lead-up to a major event, allowing drivers to be positioned nearby in advance. See www.uber.com/en-ZA/blog/scaling-michelangelo/.

4. Behavioral and Contextual Pricing (2019-Present): (1). Personalized Pricing: By 2019, Uber's AI became capable of more personalized pricing, taking into account rider-specific behaviors and preferences. While not fully individualized, the system factors personal data such as ride frequency, willingness to pay, and patterns of ride usage to offer contextual pricing. (2). Real-Time Data Integration: Uber's AI models now integrate a multitude of real-time data streams, including city traffic conditions, weather data, driver availability, and external events. The system is fully autonomous, continuously learning and adjusting pricing in real-time based on the latest inputs. See www.uber.com/blog/uber-ai-blog-2019/.

Figure A1: Timeline of AI Share of Pricing Job Posts by Uber



A.2.2 Amazon

Amazon, founded in 1994, initially started as an online bookstore. Its offerings are rapidly expanding to include electronics, clothing, and more. After going public in 1997, Amazon revolutionized e-commerce with innovations like 1-Click shopping and Amazon Prime, which fostered customer loyalty. The launch of Amazon Web Services in 2006 further diversified its business model, making it a leader in cloud computing. Over the years, Amazon has embraced data-driven strategies and algorithmic pricing to optimize operations and enhance customer experience, ultimately becoming one of the largest and most influential companies globally. Given the nature of its online retailing and cloud computing operations, Amazon sells to various customers in a very dynamic environment, making it perfectly positioned to adopt AI pricing in its operations.

Amazon AI pricing adoptions Amazon adopted algorithmic pricing, often called "dynamic pricing", early in its operations to remain competitive in the fast-paced e-commerce landscape. The shift occurred as Amazon expanded its product catalog in the early 2000s, particularly around 2007-2008, as it sought to offer the best prices to customers across millions of products. The company's algorithm pricing strategy evolved as it integrated machine learning, data analytics, and AI to adjust prices based on various factors in real-time. Its stages are as follows:

1. Initial Algorithmic Pricing (Pre-2010): Amazon began experimenting with algorithmic pricing early in its history, using software to adjust prices based on factors like supply, demand, and competitor prices. This early form of dynamic pricing was manually guided and relied on simple algorithms to optimize pricing across its vast product catalog.

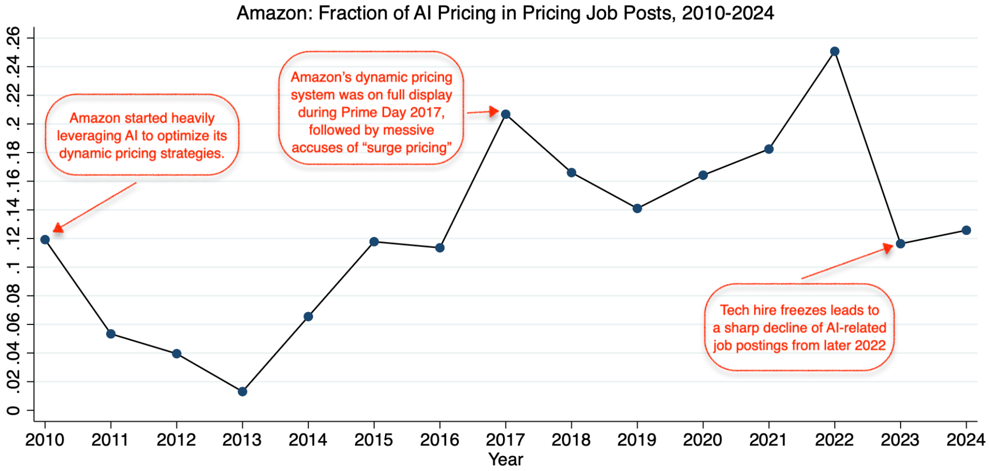
2. Introduction of Dynamic Pricing (2010-2015): Amazon developed more sophisticated dynamic pricing systems during this period. These systems used real-time data to adjust prices based on user activity, product popularity, and competitive market prices. AI started playing a larger role, allowing Amazon to implement more granular price adjustments across regions, time zones, and shopping patterns. Prime Day, launched in 2015, became a showcase of Amazon's dynamic pricing, where prices fluctuated based on live demand spikes and limited-time deals.

3. AI-Powered Personalization and Machine Learning (2016-2019): Amazon's pricing strategies became more AI-driven with the integration of machine learning. AI models began analyzing customer behavior, purchasing history, and individual preferences to offer personalized pricing and recommendations. This was especially apparent in its advertising and product suggestions, which were dynamically priced to match user intent and competitive market conditions. The system also used historical and contextual data to anticipate

demand, adjusting prices before competitors could react.

4. Advanced Predictive AI Models (2019-Present): Amazon's AI models became highly predictive, using data from millions of transactions daily. The AI now forecasts demand spikes (e.g., during holidays or product launches) and adjusts pricing preemptively to optimize sales and profits. Amazon has also fine-tuned its pricing strategy for private-label products and major events like Prime Day, where dynamic pricing becomes more aggressive. Furthermore, Amazon applies AI to optimize logistics and supply chain costs, which indirectly affects pricing.

Figure A2: Timeline of AI Share of Pricing Job Posts by Amazon



Amazon: Fraction of AI Pricing in Pricing Job Posts, 2010-2024

Amazon started heavily leveraging AI to optimize its dynamic pricing strategies.

Amazon's dynamic pricing system was on full display during Prime Day 2017, followed by messive accuses of "surge pricing"

Tech hire freezes leads to a sharp decline of AI-related job postings from later 2022

A.2.3 JPMorgan Chase

JPMorgan Chase & Co. is one of the world's largest and most influential financial institutions, with roots dating back to the 18th century. Formed through the merger of J.P. Morgan & Co. and Chase Manhattan Bank in 2000, the bank operates across investment banking, financial services, asset management, and commercial banking. Headquartered in New York City, JPMorgan Chase serves millions of customers globally, including corporations, governments, and individuals. It is known for its leadership in investment banking, financial innovation, and digital banking services, playing a critical role in global finance. The company is also actively involved in financial technology advancements and sustainable finance initiatives.

JPMorgan Chase AI pricing adoptions JPMorgan Chase has progressively adopted AI pricing technologies through several stages. Through these stages, JPMorgan Chase has evolved from basic AI applications in analytics to advanced, real-time AI pricing models that improve decision-making and customer experience across its vast financial services portfolio.

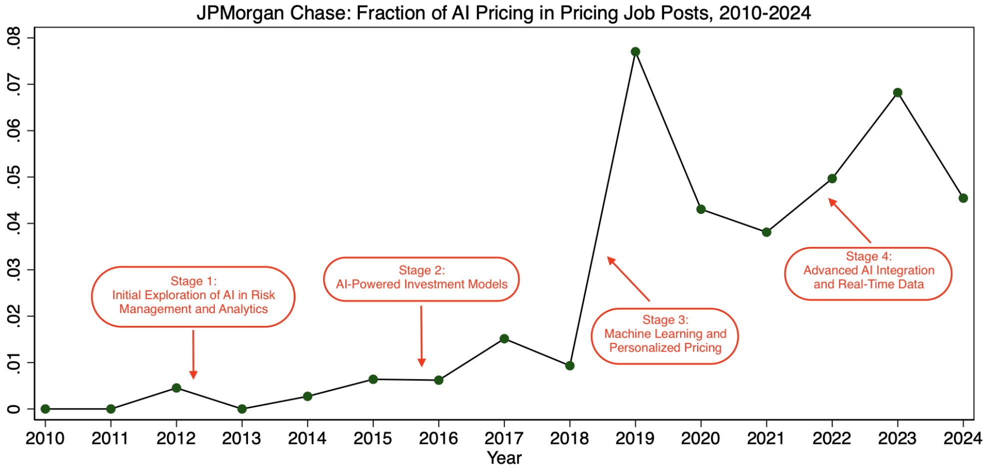
1. Initial Exploration of AI in Risk Management and Analytics (2010-2015): JPMorgan began leveraging AI primarily in risk management, credit analysis, and fraud detection. Pricing algorithms were still mostly rule-based; AI was used to analyze historical data and predict trends, laying the foundation for more dynamic pricing models.

2. AI-Powered Investment Models (2015-2018): During this period, JPMorgan implemented AI in trading and asset pricing models, particularly high-frequency trading. AI-driven pricing in investment banking helped optimize decision-making based on real-time data, including market conditions, liquidity, and client behavior. These models evolved to incorporate machine learning, which allowed for continuous learning and improvement over time.

3. Machine Learning and Personalized Pricing (2018-2020): JPMorgan started applying machine learning to refine pricing strategies in consumer banking, including mortgages and loans. By analyzing customer data, AI algorithms were used to offer personalized rates, taking into account creditworthiness, risk profiles, and market conditions. This led to more dynamic and tailored pricing strategies.

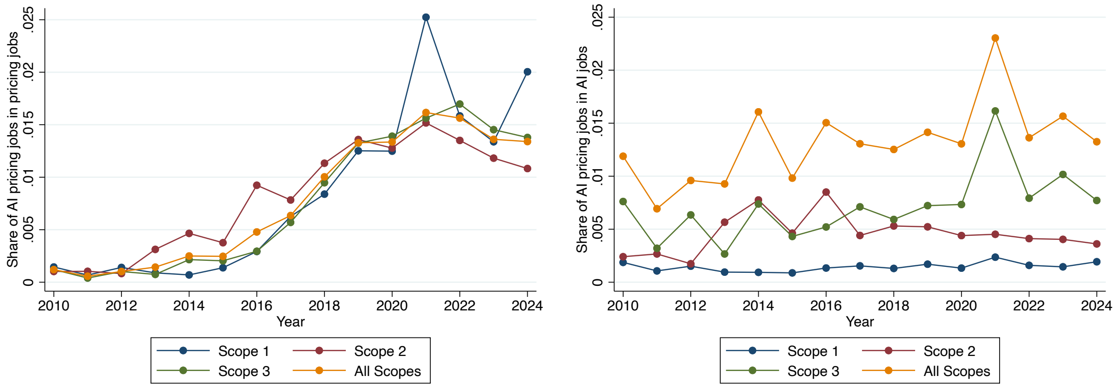
4. Advanced AI Integration and Real-Time Data (2020-Present): AI-driven pricing systems at JPMorgan now use real-time data across various services, including wealth management, investment products, and even day-to-day banking fees. AI models are capable of adjusting prices dynamically in response to market shifts, competitor actions, and customer behavior. The bank also uses AI to forecast market conditions, which helps in setting optimal pricing for both corporate clients and consumers.

Figure A3: Timeline of AI Share of Pricing Job Posts by JPMorgan Chase



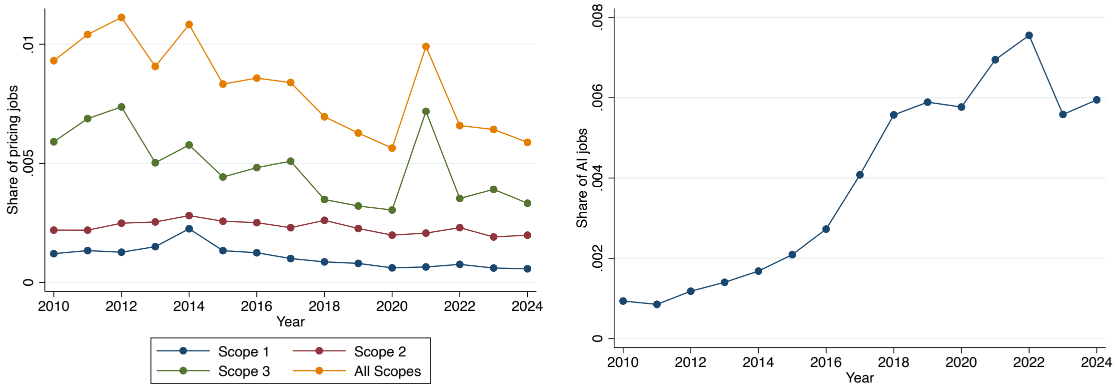
A.3 The Aggregate Trends in Alternative Measures

Figure A4: Aggregate Time Trends of AI Pricing, Pricing, and AI Jobs (Other Scopes)



(a) Share of AI Pricing in Pricing Jobs

(b) Share of AI Pricing in AI Jobs



(c) Share of Pricing Jobs in All Jobs

(d) Share of AI Jobs in All Jobs

Notes: This figure plots the aggregate time trends of AI pricing, pricing, and AI jobs, measured in different shares and scopes at annual frequency. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs are measured in three scopes. The first scope only includes the most narrowly defined pricing jobs, which must include exactly the keyword "pricing" in its job title. The second scope includes jobs with the keyword "pricing" in their specific job skill requirements. Finally, the third scope includes jobs with the keyword "pricing" in the main body of the job description, which is the most broadly defined pricing jobs. We combine all three scopes to generate an all-scope measure. Finally, we extract AI pricing jobs at the intersection of both AI-related and pricing jobs in all three scopes. With all these measures, we could construct a penal of job postings for firm j at time t. The measures include the number of jobs $N_{j,t}$, the number of AI jobs $N_{j,t}^{AI}$, the number of pricing jobs $N_{j,t}^{P_s}$ with scope $s = \{1, 2, 3, all\}$, and the number of AI pricing jobs $N_{j,t}^{AP_s}$ with scope $s = \{1, 2, 3, all\}$. We aggregate all measures to the firm level $Share_{j,t}^{x/y} = N_{j,t}^{x}/N_{j,t}^{y}$.

A.4 Leading Firms in AI Pricing

Second, we present the top thirty leading firms in the absolute number of AI pricing job postings along with two relative shares in Table A1, measured across all scopes from 2010 to 2024Q1. The table lists each company's name, the number of AI pricing job postings, the ratio of AI pricing to AI job postings, and the ratio of AI pricing to pricing job postings.

The top three firms with the most AI pricing vacancies are Deloitte, Amazon, and Uber. Deloitte leads with 1,672 total AI pricing job postings from 2010 to 2024Q1, though these make up only 6.9% of their AI vacancies and 2.4% of their pricing vacancies. Amazon follows with 1,198 AI pricing jobs, making up 15.0% of their pricing jobs, indicating significant AI integration in their pricing strategies. Uber, with 664 AI pricing jobs, demonstrates its high intensity of AI pricing adoption, with 21.1% of their AI jobs and 46.8% of their pricing jobs dedicated to AI, suggesting their dominating strategy of leveraging AI for pricing optimization.

The list also suggests a wide range of applications of AI pricing across industries: Deloitte in professional services, Amazon in technology and e-commerce, and Uber in transportation and mobility. Additionally, RealReal and Wayfair, in the retail and e-commerce sectors, show high percentages of AI pricing jobs within their pricing roles at 43.6% and 25.7%, respectively. This indicates their strong reliance on AI to enhance pricing strategies in highly competitive and dynamic markets. Traditional financial institutions like JPMorgan Chase and Wells Fargo are also on the list despite having relatively lower shares of AI pricing jobs at 2.8% and 3.3%, respectively. Notably, Rippling, a cloud-based human resources (HR) software company, stands out with exceptionally high shares of AI pricing jobs, at 74.1% of AI jobs and 94.5% of pricing jobs, signaling a deep integration of AI in their business of potential wage-setting services provided to their customers.[7] This heterogeneity reveals the substantial applicability and emerging stages of AI adoption in pricing across industries and firms.

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[7] Different from Amazon and Uber who use AI pricing on its own products, Rippling and Deloitte's AI pricing adoption could be more used on providing pricing strategies to its customers. For instance, Deloitte provides transfer pricing services for multinationals on tax avoidance. For our firm performance in later sections, we provide robustness checks to exclude these firms that hire AI pricing workers to provide services.

Table A1: Top 30 Leading Firms in AI pricing job Postings

Firm	No. of AI pricing jobs	AI Pricing/AI Jobs	AI Pricing/Pricing Jobs
Deloitte	1672	6.9%	2.4%
Amazon	1198	1.7%	15.0%
Uber	664	21.1%	46.8%
Johnson & Johnson	611	8.5%	7.2%
Accenture	427	2.8%	2.0%
The RealReal	388	7.9%	43.6%
JPMorgan Chase	344	2.7%	2.8%
CyberCoders	337	0.9%	2.8%
USAA	281	7.7%	5.8%
Capital One	273	1.1%	8.1%
Wells Fargo	251	2.2%	3.3%
Wayfair	246	18.3%	25.7%
IBM	200	1.0%	2.8%
General Motors	195	2.5%	6.0%
PricewaterhouseCoopers	186	2.5%	0.6%
Verizon Communications	147	1.7%	3.1%
UnitedHealth Group	143	2.6%	0.6%
Kforce	142	1.7%	1.2%
The Judge Group	133	3.7%	3.0%
CarMax	132	37.0%	13.9%
Target	131	10.5%	3.8%
XPO Logistics	129	28.3%	5.4%
Travelers	127	2.7%	1.2%
KPMG	119	1.7%	1.4%
Health Services Advisory Group	119	9.6%	20.6%
Zurich Insurance	114	25.4%	5.2%
Verint Systems	113	4.4%	29.6%
CVS Health	110	3.3%	1.6%
Humana	106	1.5%	1.6%
Rippling	103	74.1%	94.5%

Notes: This table shows the leading firms in the number of AI pricing job posts, measured in all scopes, from 2010 to 2024Q1. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs are measured in three scopes. The first scope only includes the most narrowly defined pricing jobs, which must include exactly the keyword "pricing" in its job title. The second scope includes jobs with the keyword "pricing" in their specific job skill requirements. Finally, the third scope includes jobs with the keyword "pricing" in the main body of the job description, which is the most broadly defined pricing jobs. We combine all three scopes to generate an all-scope measure. Finally, we extract AI pricing jobs at the intersection of both AI-related and pricing jobs in all three scopes.

A.5 Leading Firms in AI Pricing in Alternative Measures

Below, we check the top thirty leading firms in AI pricing job postings in different scopes.

Table A2: Top 30 Leading Firms in AI pricing jobs (Scope 1)

Company	No. AI pricing jobs	AI Pricing/AI Jobs	AI Pricing/Pricing Jobs
Uber	256	8.1%	58.3%
Amazon	231	0.3%	16.1%
Johnson & Johnson	93	1.3%	16.1%
JPMorgan Chase	54	0.4%	3.0%
CarMax	47	13.2%	43.1%
Target	47	3.8%	8.7%
Zurich Insurance	37	8.3%	6.9%
XPO Logistics	35	7.7%	6.7%
Opendoor	32	30.8%	21.2%
The RealReal	28	0.6%	47.5%
CVS Health	28	0.8%	4.3%
Ingram Micro	27	24.8%	30.0%
Wayfair	27	2.0%	19.3%
Cigna	26	1.9%	13.9%
Sap&Sap Corp	25	1.3%	32.9%
Walmart	25	0.4%	6.3%
Staples	23	4.3%	2.7%
Travelers	21	0.4%	5.0%
Nordstrom	21	3.9%	72.4%
Bloomberg	21	1.2%	8.3%
Kosmix	20	13.0%	100.0%
Kforce	20	0.2%	1.5%
Citigroup	19	0.4%	3.3%
Matson	18	20.7%	72.0%
Thomas Publishing	17	81.0%	100.0%
Affirm	17	6.1%	28.8%
McKinsey	16	2.1%	25.4%
Expedia Group	15	1.2%	7.8%
PricewaterhouseCoopers	15	0.2%	0.7%
Automation Anywhere	15	1.4%	88.2%

Scope 1: Pricing in Job Titles Table A2 presents the top 30 companies leading in AI pricing jobs (Scope 1) based on three key metrics. Uber ranks first with 256 AI pricing jobs, followed by Amazon with 231, while companies like Johnson & Johnson (93), JPMorgan Chase (54), and CarMax (47) also feature prominently. The AI Pricing/AI Jobs Ratio, which reflects the proportion of AI pricing jobs out of a company's total AI jobs, is highest at Thomas Publishing (81%), Opendoor (30.8%), and Ingram Micro (24.8%). Additionally, the AI Pricing/Pricing Jobs Ratio, which shows the share of AI pricing jobs among total pricing jobs, is led by Kosmix and Thomas Publishing, both at 100%, followed by Automation Anywhere at 88.2%. While Uber and Amazon dominate in absolute numbers, smaller firms like Kosmix and Thomas Publishing have a much

higher concentration of AI pricing jobs than their total AI and pricing jobs.

Table A3: Top 30 Leading Firms in AI pricing jobs (Scope 2)

Company	No. AI pricing jobs	AI Pricing/AI Jobs	AI Pricing/Pricing Jobs
Deloitte	1038	4.3%	1.9%
Accenture	344	2.3%	5.2%
Amazon	299	0.4%	10.7%
Capital One	228	0.9%	8.6%
Johnson & Johnson	222	3.1%	6.8%
PricewaterhouseCoopers	123	1.7%	0.6%
Verint Systems	113	4.4%	39.6%
KPMG	82	1.2%	3.0%
Wayfair	69	5.1%	32.2%
IBM	68	0.3%	2.3%
Goldman Sachs	61	3.2%	8.4%
Postmates	61	26.6%	92.4%
Nvidia	59	0.7%	37.6%
UnitedHealth Group	59	1.1%	1.6%
JPMorgan Chase	57	0.5%	1.6%
Wells Fargo	57	0.5%	2.1%
The RealReal	49	1.0%	28.5%
Bank of America	46	0.4%	3.1%
Ernst & Young	45	2.5%	1.1%
Automation Anywhere	45	4.2%	52.9%
CarMax	38	10.6%	24.5%
CyberCoders	37	0.1%	1.8%
Zurich Insurance	37	8.3%	10.0%
XPO Logistics	36	7.9%	6.7%
Uber	35	1.1%	15.5%
BDO	34	12.1%	4.3%
Lumen Technologies	33	1.4%	6.3%
Kforce	32	0.4%	1.3%
Cognizant Technology Solutions	31	1.6%	11.9%
Celestica	30	52.6%	20.8%

Scope 2: Pricing in Skill Requirements Table A3 highlights the top 30 companies leading in AI pricing jobs (Scope 2), focusing on the number of AI pricing jobs, the percentage of AI pricing jobs compared to total AI jobs, and the share of AI pricing jobs within overall pricing roles. Deloitte tops the list with 1,038 AI pricing jobs, followed by Accenture with 344, Amazon with 299, Capital One with 228, and Johnson & Johnson with 222. Celestica has the highest proportion of AI pricing jobs relative to its total AI jobs at 52.6%, with Postmates (26.6%) and Wayfair (5.1%) also showing strong AI pricing job concentration. In terms of AI pricing jobs within overall pricing roles, Postmates leads with 92.4%, followed by Automation Anywhere (52.9%) and Verint Systems (39.6%). While Deloitte and Accenture have the highest number of AI pricing jobs, companies like Postmates and Celestica have a much higher concentration of AI pricing jobs in their categories.

Table A4: Top 30 Leading Firms in AI pricing jobs (Scope 3)

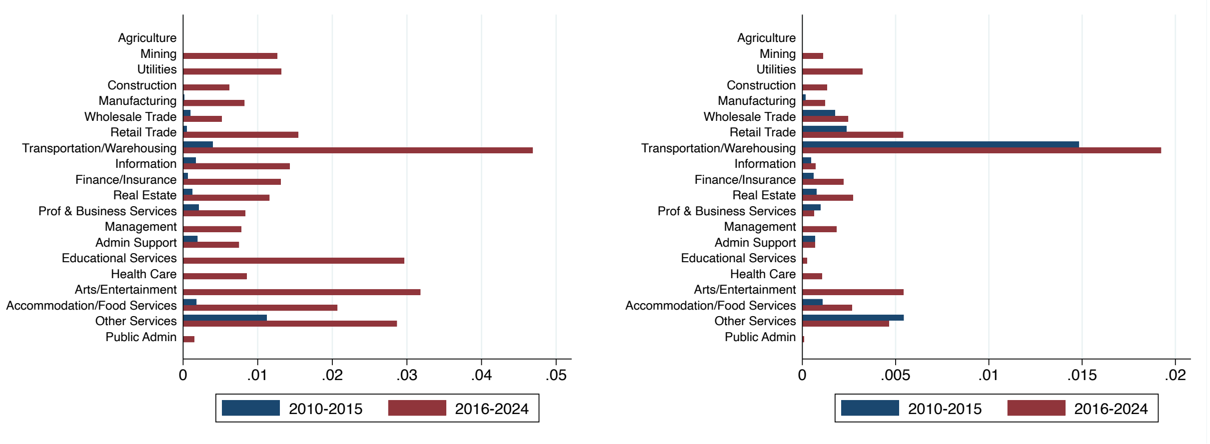
Company	No. AI pricing jobs	AI Pricing/AI Jobs	AI Pricing/Pricing Jobs
Amazon	668	0.9%	17.7%
Deloitte	632	2.6%	4.6%
Uber	373	11.9%	49.4%
The RealReal	311	6.3%	47.2%
Johnson & Johnson	296	4.1%	6.4%
CyberCoders	293	0.8%	3.1%
USAA	263	7.2%	7.4%
JPMorgan Chase	233	1.8%	3.2%
General Motors	190	2.5%	7.3%
Wells Fargo	189	1.6%	4.3%
Wayfair	150	11.2%	24.8%
IBM	129	0.6%	3.3%
Verizon Communications	127	1.5%	5.3%
Health Services Advisory Group	119	9.6%	20.6%
The Judge Group	118	3.3%	3.3%
Humana	104	1.5%	2.4%
Rippling	103	74.1%	98.1%
PayPal	99	6.2%	6.7%
Insurance Services Office	96	7.7%	61.9%
Kforce	90	1.1%	1.2%
Travelers	83	1.8%	1.0%
Accenture	82	0.5%	0.6%
UnitedHealth Group	77	1.4%	0.4%
The Boston Consulting Group (BCG)	76	4.8%	5.5%
Bloomberg	74	4.3%	7.5%
Target	72	5.8%	2.8%
Liberty Mutual	66	7.0%	6.0%
Walmart	63	0.9%	4.6%
Nationwide	60	9.5%	6.7%
Chewy	60	5.4%	14.1%

Scope 3: Pricing in Job Description Table A4 highlights the top 30 companies leading in AI pricing jobs (Scope 3), focusing on the number of AI pricing jobs, the percentage of AI pricing jobs relative to total AI jobs, and the share of AI pricing jobs within overall pricing roles. Amazon leads with 668 AI pricing jobs, followed by Deloitte with 632, Uber with 373, The RealReal with 311, and Johnson & Johnson with 296. Rippling has the highest concentration of AI pricing jobs relative to its total AI jobs at 74.1%, with Uber (11.9%) and Wayfair (11.2%) also showing strong AI pricing job concentrations. In terms of AI pricing jobs within overall pricing roles, Rippling leads with 98.1%, followed by Insurance Services Office (61.9%) and Uber (49.4%). While Amazon and Deloitte have the most AI pricing jobs, companies like Rippling and Uber have a significantly higher concentration of AI pricing jobs within their total AI and pricing job categories.

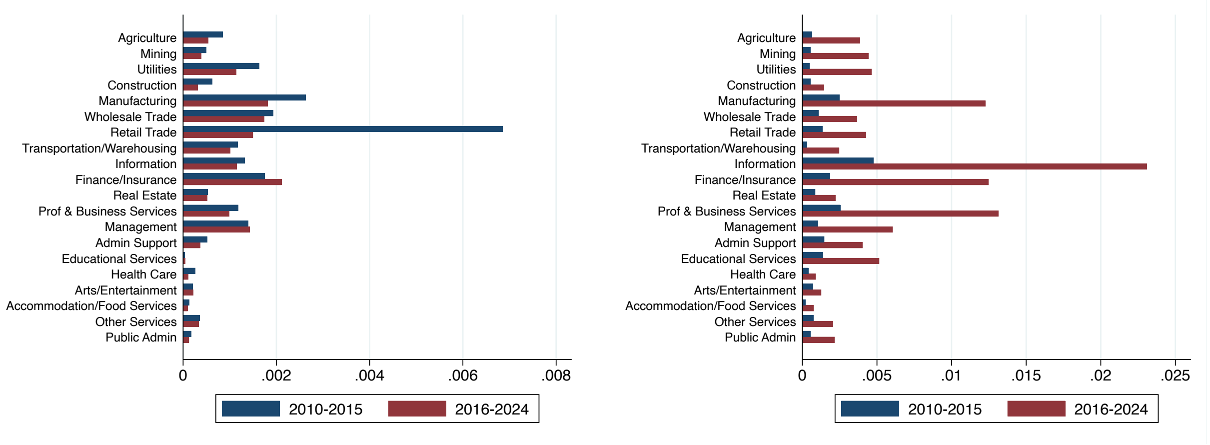
A.6 Variations Across Industries of AI Pricing

Below, we check the variations across two-digit level industries in AI pricing job postings in different scopes. In all three different scopes, we see a dominant growth of AI pricing jobs in transportation, information, finance, and business services. In contrast, industries such as agriculture, mining, and construction maintained consistently low shares of AI pricing jobs across time, indicating limited applicability or slower adoption of AI in pricing within these sectors.

Figure A5: Variations Across Two Digit Industry Sector (Scope 1)



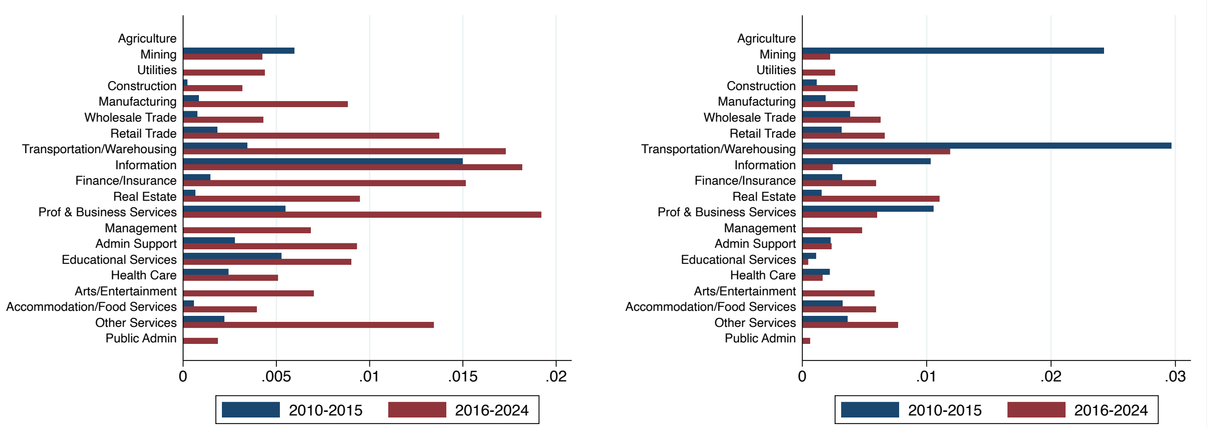
(a) Share of AI Pricing in Pricing Jobs (Scope 1) (b) Share of AI Pricing in AI Jobs (Scope 1)



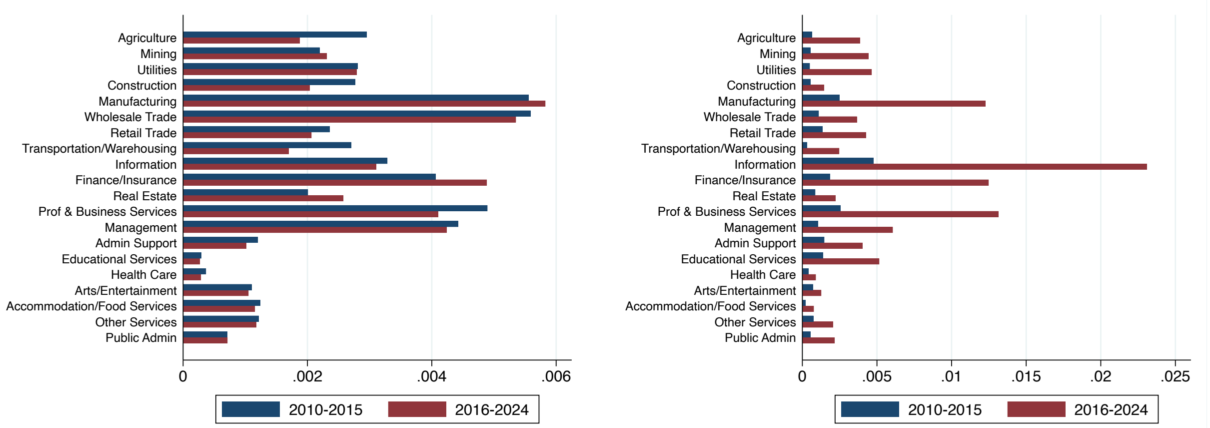
(c) Share of Pricing Jobs (Scope 1) (d) Share of AI Jobs

Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs, measured in different shares and scopes for two periods: 2010-2015 and 2016-2024. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs only include the most narrowly defined pricing jobs, which must include exactly the keyword "pricing" in their job title. The construction of the ratios follows the same process as in Table 2 in the main paper.

Figure A6: Variations Across Two Digit Industry Sector (Scope 2)



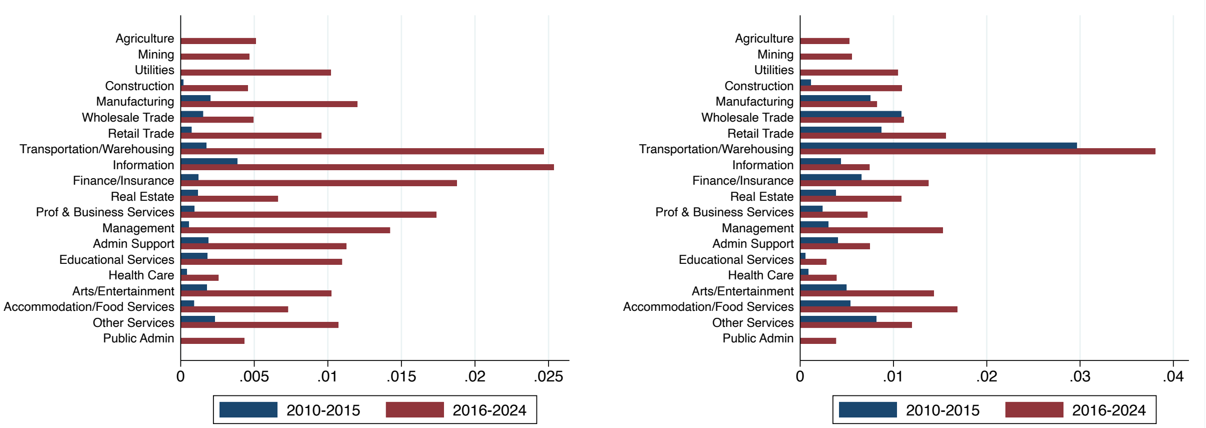
(a) Share of AI Pricing in Pricing Jobs (Scope 2) (b) Share of AI Pricing in AI Jobs (Scope 2)



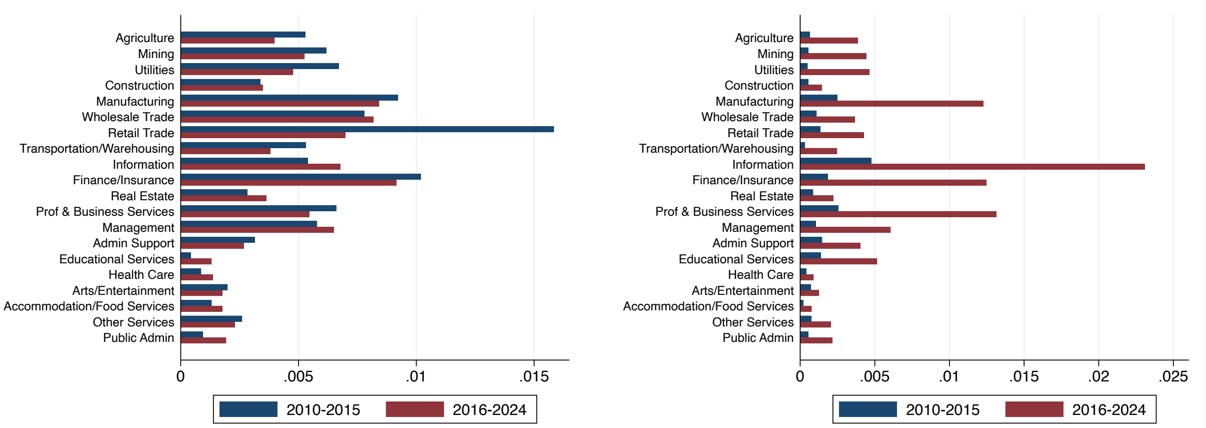
(c) Share of Pricing Jobs (Scope 2) (d) Share of AI Jobs

Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs, measured in different shares and scopes for two periods: 2010-2015 and 2016-2024. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs only include jobs with the keyword "pricing" in their specific job skill requirements. The construction of the ratios follows the same process as in Table 2 in the main paper.

Figure A7: Variations Across Two Digit Industry Sector (Scope 3)



(a) Share of AI Pricing in Pricing Jobs (Scope 3) (b) Share of AI Pricing in AI Jobs (Scope 3)



(c) Share of Pricing Jobs (Scope 3) (d) Share of AI Jobs

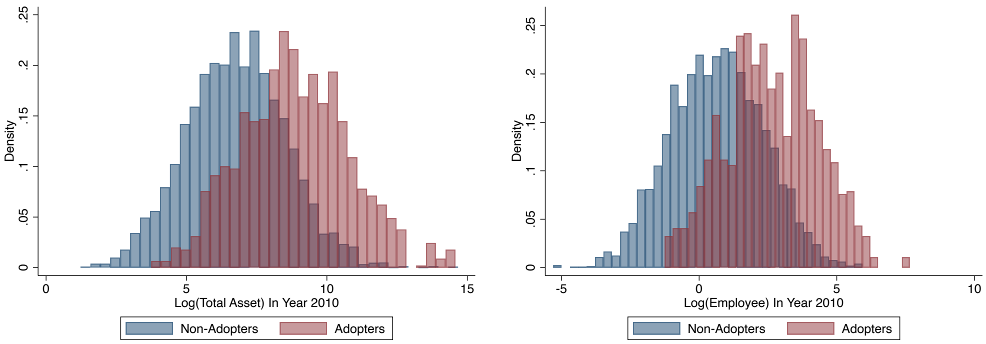
Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs, measured in different shares and scopes for two periods: 2010-2015 and 2016-2024. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs only include jobs with the keyword "pricing" in the main body of the job description, which is the most broadly defined pricing job. The construction of the ratios follows the same process as in Table 2 in the main paper.

B Supplements to Firm-level Determinants

B.1 Distributions of AI Pricing Adopters and Non-Adopters

Other Measures of Firm Size Figure B1 presents the size distributions of AI pricing adopters and non-adopters in 2010, comparing their total assets (left) and employee numbers (right) in log scale. The histograms show that adopters (in red) tend to have larger total assets and more employees than non-adopters (in blue), indicating that firms that adopt AI pricing technologies tend to be larger. The notes clarify that adopters are firms that have posted at least one AI pricing job by 2024 Q1, while non-adopters have not done so.

Figure B1: Size Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



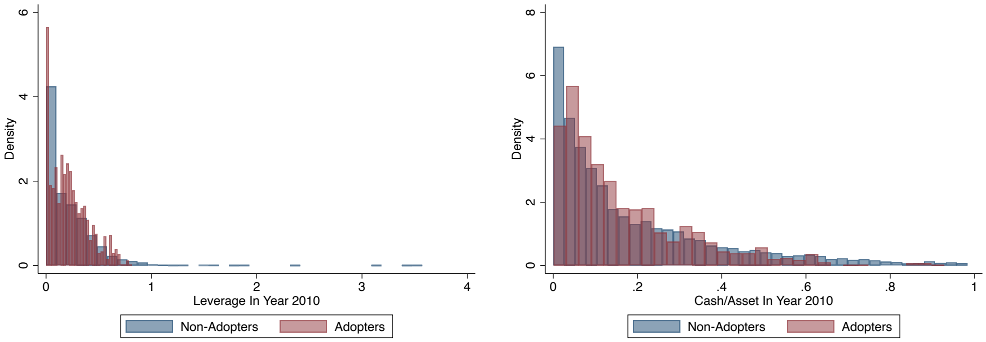
(a) Log Total Asset Distribution (b) Log Employee Distribution

Notes: An adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 1$) is a firm j that posted at least one AI pricing job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 0$) is a firm j that never posted AI pricing job since the beginning of our data sample until 2024Q1. We provide a comparison to AI adoption in Figure B5.

Financial Conditions Measures Figure B2 shows the financial distributions of AI pricing adopters and non-adopters in 2010, focusing on leverage (left) and cash/assets ratios (right). The leverage distribution (a) reveals that non-adopters (blue) generally have higher leverage compared to adopters (red), especially near zero. The cash/assets distribution (b) indicates that non-adopters tend to have slightly higher cash-to-asset ratios, though the differences are less pronounced. Adopters appear to have a more spread-out distribution across both metrics. As in the previous figure, adopters are defined as firms posting AI pricing jobs by 2024 Q1, and non-adopters have not done so.

Operational Conditions Measures Figure B3 illustrates the operational distributions of AI pricing adopters and non-adopters in 2010, focusing on Tobin's Q (left) and markup (right) in log scale. Tobin's Q distribution (a measure of firm value) shows that adopters (red) and non-

Figure B2: Financial Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



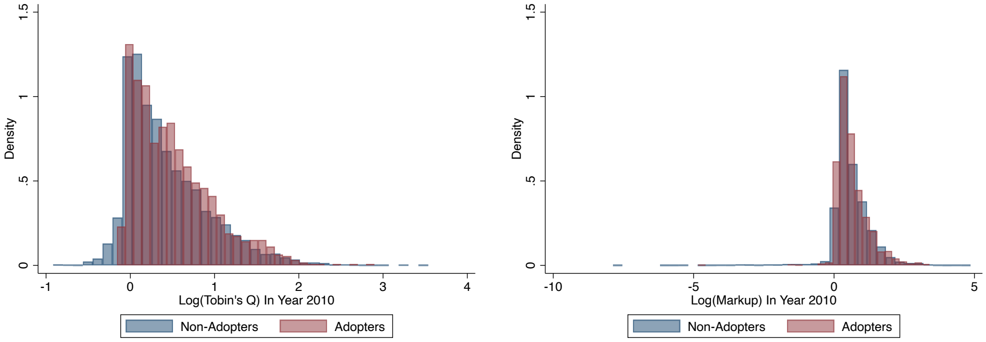
(a) Leverage Distribution

(b) Cash/Asset Distribution

Notes: An adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 1$) is a firm j that posted at least one AI pricing job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 0$) is a firm j that never posted AI pricing job since the beginning of our data sample until 2024Q1. We provide a comparison of AI adoption in Figure B6.

adopters (blue) have relatively similar distributions, with a slight tendency for adopters to have higher values. The markup distribution (b) also shows similar patterns between the two groups, with both concentrated around zero. As with previous figures, adopters are firms that posted AI pricing jobs by 2024 Q1, while non-adopters have not.

Figure B3: Operational Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



(a) Log Tobin's Q Distribution

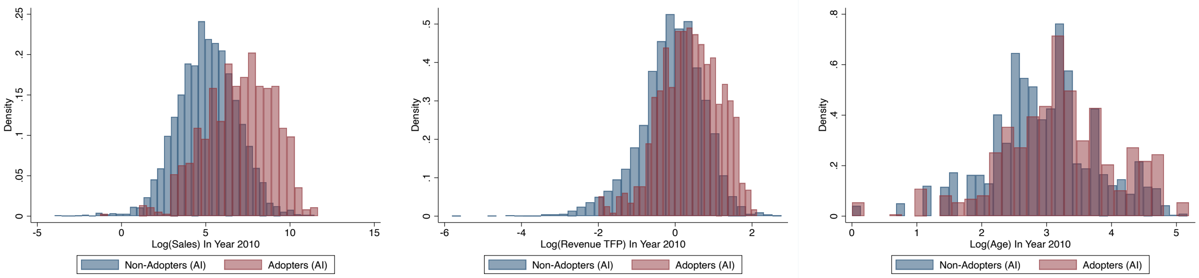
(b) Log Markup Distribution

Notes: An adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 1$) is a firm j that posted at least one AI pricing job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AP}_{j,2024Q1} = 0$) is a firm j that never posted AI pricing job since the beginning of our data sample until 2024Q1. We provide a comparison to AI adoption in Figure B7.

B.2 Distributions of General AI Adopters and Non-Adopters

Size, Productivity, and Age Measures Figure B4 shows three distributions comparing AI adopters and non-adopters in 2010 across different metrics. Graph (a) displays the size distribution based on log(Sales), where AI adopters tend to have higher sales figures than non-adopters. Graph (b) presents the TFP (Total Factor Productivity) distribution, indicating that AI adopters generally have higher TFP values. Graph (c) illustrates the age distribution of firms, suggesting that AI adopters are slightly older on average than non-adopters. In all three graphs, the distributions for AI adopters (shown in red) are shifted somewhat to the right compared to non-adopters (shown in blue), implying that firms adopting AI tend to be larger, more productive, and slightly older than those not adopting AI.

Figure B4: Distributions of AI Adopters and Non-Adopters In the Year 2010



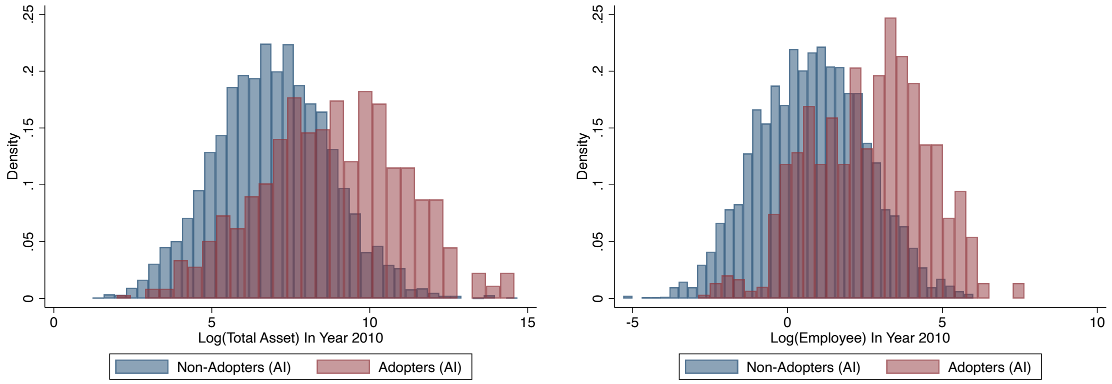
(a) Size Distribution (b) TFP Distribution (c) Age Distribution

Notes: These figures compare AI adoption to the AI pricing adoption distribution in Figure 3. An AI adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 1$) is a firm j that posted at least one AI job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 0$) is a firm j that never posted AI job since the beginning of our data sample until 2024Q1.

Other Measures of Firm Size Figure B5 compares the size distributions of AI adopters and non-adopters in 2010 using two metrics: total assets and number of employees. Graph (a) shows the distribution of log(Total Asset), while graph (b) displays the distribution of log(Employee). In both graphs, the distribution for AI adopters (shown in red) is shifted to the right compared to non-adopters (shown in blue). This indicates that firms adopting AI tend to have larger total assets and more employees than those not adopting AI. The difference is particularly pronounced in the total asset distribution, where AI adopters have a noticeably higher concentration in the upper ranges. Overall, the graphs suggest that larger companies, regarding assets and workforce, were more likely to adopt AI technologies.

Financial Conditions Measures Figure B6 compares the financial distributions of AI adopters and non-adopters in 2010 using two metrics: leverage and cash/asset ratio. Graph (a) shows the leverage distribution, where AI adopters and non-adopters have similar patterns, with a high

Figure B5: Size Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010

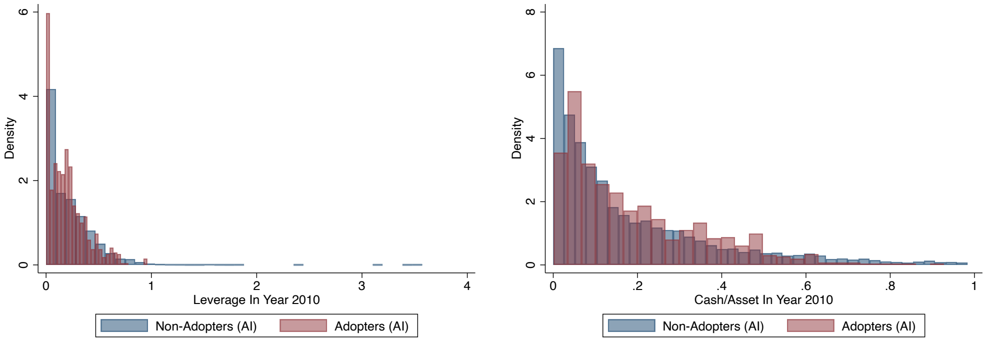


(a) Log Total Asset Distribution

(b) Log Employee Distribution

Notes: These figures compare AI adoption to the AI pricing adoption distribution in Figure B1. An AI adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 1$) is a firm j that posted at least one AI job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 0$) is a firm j that never posted AI job since the beginning of our data sample until 2024Q1.

Figure B6: Financial Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



(a) Leverage Distribution

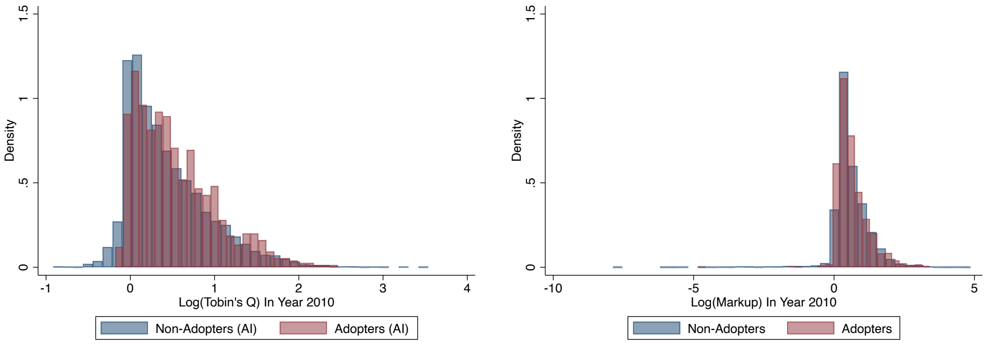
(b) Cash/Asset Distribution

Notes: These figures compare AI adoption to the AI pricing adoption distribution in Figure B2. An AI adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 1$) is a firm j that posted at least one AI job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 0$) is a firm j that never posted AI job since the beginning of our data sample until 2024Q1.

concentration of firms at lower leverage levels. However, AI adopters (in red) show a slightly higher density at very low leverage levels. Graph (b) displays the cash/asset distribution, where both groups again show similar overall patterns, with a high concentration of firms having lower cash/asset ratios. There's a subtle indication that AI adopters might have a slightly more dispersed distribution in cash/asset ratios, with a bit more representation in higher ratio ranges. Overall, the financial distributions suggest only minor differences between AI adopters and non-adopters regarding leverage and cash/asset ratios, with AI adopters potentially having slightly lower leverage and more varied cash/asset positions.

Operational Conditions Measures Figure B7 compares the operational distributions of AI adopters and non-adopters in 2010 using two metrics: Log(Tobin's Q) and Log(Markup). Graph (a) shows the Log(Tobin's Q) distribution, where AI adopters (in red) have a slightly higher and more right-skewed distribution compared to non-adopters (in blue), suggesting that AI adopters tend to have higher market valuations relative to their book values. Graph (b) displays the Log(Markup) distribution, which is more tightly clustered around 0 for both groups, but AI adopters show a slightly higher density in the positive range, indicating potentially higher profit margins. In both graphs, the differences between adopters and non-adopters are subtle but noticeable, with AI adopters generally showing slightly more favorable operational metrics.

Figure B7: Operational Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



(a) Log Tobin's Q Distribution

(b) Log Markup Distribution

Notes: These figures compare AI adoption to the AI pricing adoption distribution in Figure B3. An AI adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 1$) is a firm j that posted at least one AI job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 0$) is a firm j that never posted AI job since the beginning of our data sample until 2024Q1.

B.3 Firm-level Determinants of AI pricing adoption in Sub-periods

To test whether the firm-level determinants of AI pricing adoption are consistent over time, we cut our sample into two sub-periods as we document the across-industry variations: 2010-2015 and 2016-2024. The two sets of specifications are as follows:

$$\textbf{Sub-period 1:} \quad \{\mathbb{1}^{AP}_{j,2015Q4}, APN_{j,2015Q4}, APS_{j,2015Q4}\} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq},$$

$$\textbf{Sub-period 2:} \quad \{\mathbb{1}^{AP}_{j,2024Q1}, APN_{j,2024Q1}, APS_{j,2024Q1}\} = \beta x_{j,2016q} + \gamma_s + \delta_q + \epsilon_{jq},$$

where j represents firms, q is one of the four quarters, and s refers to two-digit NAICS sectors. The dependent variables are firm j's AI pricing adoption indicator, which equals one if the firm posts at least one AI pricing vacancy within the subperiod. The independent variables represents firm j's characteristic in quarter q of 2010 or 2016, for $q = Q1, Q2, Q3, Q4$. The characteristics examined include logged sales, logged TFP, logged age, Tobin's Q, logged markup, the ratio of R&D to sales, ROA, cash-to-assets ratio, and debt-to-assets ratio, all winsorized at the top and bottom 1% at the year quarter frequency.[8] We also include industry fixed effects (γ_s) and quarter fixed effects (δ_q) to control for unobserved heterogeneity.

Sub-period 1: 2010-2015 Tables B1, B2, and B3 report the results of sub-period 1 for dependent variables $\{\mathbb{1}^{AP}_{j,2015Q4}, APN_{j,2015Q4}, APS_{j,2015Q4}\}$, respectively. Standard errors are in parentheses. Significance: * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The sub-period results are generally consistent with the results in the main paper.

Sub-period 2: 2016-2024 Tables B4, B5, and B6 report the results of sub-period 2 for dependent variables $\{\mathbb{1}^{AP}_{j,2024Q1}, APN_{j,2024Q1}, APS_{j,2024Q1}\}$, respectively. Standard errors are in parentheses. Significance: * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The sub-period results are generally consistent with the results in the main paper.

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[8] Tobin's Q is calculated as tobinq $= (\text{prccq} \times \text{cshoq} - \text{ceqq} + \text{atq})/\text{atq}$, where the market value of the firm's assets ($\text{prccq} \times \text{cshoq}$) is adjusted by subtracting the book value of equity (ceqq) and adding total assets (atq), then divided by total assets (atq). Makrup is calculated as the ratio of sales to costs of goods sode.

Table B1: Firm-level Determinants of AI pricing adoption

	AI Pricing Adopter Dummy Indicator, 2010-2015Q4 ($\mathbb{1}^{AP}_{j,2015Q4} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.022***									0.031***
	(0.001)									(0.003)
Log TFP 2010		0.032***								0.023***
		(0.003)								(0.007)
Log Age 2010			0.013***							0.017***
			(0.003)							(0.005)
Tobin's Q 2010				-0.000						-0.004*
				(0.001)						(0.003)
Log Markup 2010					0.002					-0.010
					(0.003)					(0.010)
R&D/Sales 2010						-0.000				0.078**
						(0.000)				(0.038)
ROA 2010							-0.065*			0.010
							(0.039)			(0.080)
Cash/Assets 2010								-0.006		0.024
								(0.011)		(0.025)
Debt/Assets 2010									0.010	0.022
									(0.009)	(0.021)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	3790	7776	7787	7299	3021
adj. R^2	0.067	0.035	0.021	0.017	0.017	0.019	0.017	0.017	0.014	0.098

Table B2: Firm-level Determinants of Cumulative AI pricing job Postings

	Total AI pricing job Postings, 2010-2015Q4 ($APN_{j,2015Q4}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.220***									0.301***
	(0.027)									(0.068)
Log TFP 2010		0.456***								0.505***
		(0.069)								(0.177)
Log Age 2010			0.076							0.270**
			(0.062)							(0.127)
Tobin's Q 2010				0.129***						0.034
				(0.036)						(0.067)
Log Markup 2010					0.048					-0.516**
					(0.078)					(0.247)
R&D/Sales 2010						-0.000				1.651*
						(0.004)				(0.987)
ROA 2010							-0.537			-0.425
							(0.931)			(2.072)
Cash/Assets 2010								0.298		-0.057
								(0.265)		(0.641)
Debt/Assets 2010									0.290	0.969*
									(0.189)	(0.557)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	3790	7776	7787	7299	3021
adj. R^2	0.019	0.016	0.012	0.012	0.010	0.012	0.010	0.010	0.005	0.027

Table B3: Firm-level Determinants of Cumulative AI pricing job Postings Intensity

	Total AI pricing job Postings/Total Pricing Job Postings, 2010Q1-2015Q4 ($APS_{j,2015Q4}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	-0.001*									-0.003**
	(0.000)									(0.001)
Log TFP 2010		0.003***								0.009***
		(0.001)								(0.003)
Log Age 2010			-0.003***							-0.007***
			(0.001)							(0.002)
Tobin's Q 2010				-0.000						-0.002*
				(0.000)						(0.001)
Log Markup 2010					0.001					-0.010***
					(0.001)					(0.004)
R&D/Sales 2010						-0.000				0.022
						(0.000)				(0.015)
ROA 2010							-0.008			-0.015
							(0.019)			(0.042)
Cash/Assets 2010								0.006*		-0.005
								(0.004)		(0.010)
Debt/Assets 2010									0.001	0.020**
									(0.003)	(0.008)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5601	5267	5320	5607	5588	2764	5601	5607	5297	2340
adj. R^2	0.002	0.003	0.004	0.002	0.002	-0.001	0.002	0.002	0.002	0.011

Table B4: Firm-level Determinants of AI pricing adoption

	AI Pricing Adopter Dummy Indicator, 2016-2024Q1 ($\mathbb{1}^{AP}_{j,2024Q1} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2016	0.081***									0.111***
	(0.002)									(0.004)
Log TFP 2016		0.100***								0.012
		(0.005)								(0.011)
Log Age 2016			0.037***							0.013*
			(0.005)							(0.007)
Tobin's Q 2016				0.023***						0.015***
				(0.003)						(0.004)
Log Markup 2016					0.011**					0.036**
					(0.004)					(0.015)
R&D/Sales 2016						-0.000				0.024***
						(0.000)				(0.009)
ROA 2016							-0.341***			0.487***
							(0.066)			(0.153)
Cash/Assets 2016								-0.063***		0.169***
								(0.020)		(0.041)
Debt/Assets 2016									0.094***	0.025
									(0.017)	(0.031)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	9179	8004	8641	9324	9160	4492	9325	9328	8734	3333
adj. R^2	0.197	0.063	0.030	0.034	0.026	0.030	0.029	0.027	0.028	0.246

Table B5: Firm-level Determinants of Cumulative AI pricing job Postings

	Total AI pricing job Postings, 2016-2024Q1($APN_{j,2024Q1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2016	3.139***									5.559***
	(0.157)									(0.515)
Log TFP 2016		4.114***								2.463*
		(0.450)								(1.324)
Log Age 2016			0.958**							-0.989
			(0.379)							(0.899)
Tobin's Q 2016				0.984***						1.378***
				(0.208)						(0.500)
Log Markup 2016					0.148					-3.359*
					(0.357)					(1.812)
R&D/Sales 2016						-0.001				1.568
						(0.004)				(1.079)
ROA 2016							-10.167*			23.324
							(5.279)			(18.392)
Cash/Assets 2016								1.215		14.818***
								(1.569)		(4.964)
Debt/Assets 2016									1.736	-7.838**
									(1.387)	(3.698)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	9179	8004	8641	9324	9160	4492	9325	9328	8734	3333
adj. R^2	0.054	0.022	0.014	0.015	0.013	0.018	0.013	0.013	0.013	0.068

Table B6: Firm-level Determinants of Cumulative AI pricing job Postings Intensity

	Total AI pricing job Postings/Total Pricing Job Postings, 2016Q1-2024Q4 ($APS_{j,2024Q1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2016	0.001***									0.002***
	(0.000)									(0.001)
Log TFP 2016		0.004***								0.006***
		(0.001)								(0.002)
Log Age 2016			-0.001*							-0.002
			(0.001)							(0.001)
Tobin's Q 2016				0.002***						0.000
				(0.000)						(0.001)
Log Markup 2016					-0.001					-0.010***
					(0.001)					(0.003)
R&D/Sales 2016						-0.000				-0.001
						(0.000)				(0.006)
ROA 2016							0.021			0.080**
							(0.015)			(0.032)
Cash/Assets 2016								0.013***		0.036***
								(0.003)		(0.008)
Debt/Assets 2016									0.001	-0.000
									(0.003)	(0.005)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7449	6804	7127	7531	7438	3647	7535	7535	7097	2934
adj. R^2	0.015	0.018	0.015	0.016	0.014	0.017	0.014	0.016	0.016	0.037

C Supplements to Firm Performance

C.1 Additional Firm Performance Results from Long-differences

C.1.1 Heterogeneity Among Industries

We examine the long-difference regressions by industry at the NAICS two-digit level. In some industries, AI pricing is associated with both firm growth and markup growth; in some industries, AI pricing is associated with either firm growth or markup growth; finally, in other industries, neither is robustly significant. However, since some regressions' sample size is too small, we cannot be sure if the drops in significance are due to changes in economic mechanisms or simply because of sample size.

Table C1: AI Pricing and Firm Performance: Long-differences by Industry, Part I

	Manufacturing				Wholesale & Retail			
	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	3.862***	2.666***	3.807***	1.086***	2.639*	3.815***	3.783***	0.694***
	(0.695)	(0.592)	(0.750)	(0.239)	(1.351)	(1.107)	(1.354)	(0.237)
Share of AI	-0.889	-0.938	-0.925	-1.332***	63.887***	56.891***	59.272***	16.442***
	(0.743)	(0.629)	(0.801)	(0.255)	(17.303)	(14.377)	(17.337)	(3.037)
Share of Pricing	1.193***	1.404***	1.366***	1.033***	-0.656	0.088	0.127	-0.757***
	(0.443)	(0.394)	(0.478)	(0.152)	(1.239)	(1.034)	(1.241)	(0.217)
Log Sales	-0.086***	-0.133***	-0.122***	0.008	-0.027	-0.033	-0.063**	0.000
	(0.015)	(0.013)	(0.016)	(0.005)	(0.031)	(0.028)	(0.031)	(0.005)
Log TFP	-0.198***	0.042	-0.118***	-0.090***	-0.010	0.129	0.045	-0.045***
	(0.032)	(0.029)	(0.035)	(0.011)	(0.096)	(0.095)	(0.096)	(0.017)
Log Age	-0.115***	-0.132***	-0.124***	0.006	-0.039	-0.040	-0.116**	-0.028***
	(0.025)	(0.022)	(0.027)	(0.009)	(0.049)	(0.042)	(0.049)	(0.009)
Tobin's Q	0.726***	0.511***	0.884***	0.020	0.481***	0.361***	0.476***	-0.058***
	(0.056)	(0.050)	(0.060)	(0.019)	(0.121)	(0.109)	(0.121)	(0.021)
Cash/Assets	0.391**	0.229	-0.122	0.213***	-2.807***	-1.509***	-2.253***	-0.133*
	(0.157)	(0.144)	(0.169)	(0.054)	(0.407)	(0.374)	(0.408)	(0.071)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	1456	1314	1457	1456	377	334	377	377
adj. R^2	0.241	0.282	0.245	0.098	0.184	0.211	0.176	0.142

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

Table C2: AI Pricing and Firm Performance: Long-differences by Industry, Part II

	Transportation & Warehousing				Information Technology			
	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.951**	1.543***	0.933	-0.174	3.788*	0.294	11.262***	4.783***
	(0.742)	(0.549)	(0.850)	(0.139)	(2.257)	(3.667)	(2.625)	(1.207)
Share of AI	-30.446	-21.728	-47.795	-3.849	-0.502	4.976	-3.165	-6.439
	(33.621)	(24.379)	(38.489)	(6.301)	(7.300)	(5.931)	(8.488)	(3.902)
Share of Pricing	1.904	1.432	2.965**	0.565**	-0.389	-0.546	-0.737	-0.995**
	(1.277)	(0.949)	(1.461)	(0.239)	(0.826)	(0.657)	(0.960)	(0.442)
Log Sales	-0.089*	-0.090**	-0.167***	0.029***	-0.058*	-0.140***	-0.051	0.034*
	(0.048)	(0.038)	(0.054)	(0.009)	(0.034)	(0.030)	(0.040)	(0.018)
Log TFP	0.149*	0.091	0.239***	-0.020	0.152*	0.370***	0.044	-0.194***
	(0.077)	(0.072)	(0.089)	(0.015)	(0.086)	(0.070)	(0.099)	(0.046)
Log Age	-0.416***	-0.217***	-0.378***	-0.018	-0.281***	-0.316***	-0.278***	0.042
	(0.070)	(0.051)	(0.080)	(0.013)	(0.072)	(0.061)	(0.084)	(0.039)
Tobin's Q	-0.243*	-0.004	-0.231	0.040*	0.683***	0.467***	1.107***	-0.065
	(0.127)	(0.097)	(0.146)	(0.024)	(0.134)	(0.116)	(0.156)	(0.072)
Cash/Assets	0.469	1.444***	1.004*	-0.446***	-0.667*	-1.023***	-0.763*	0.416**
	(0.469)	(0.357)	(0.537)	(0.088)	(0.349)	(0.307)	(0.406)	(0.187)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	105	96	105	105	256	211	256	256
adj. R^2	0.345	0.349	0.327	0.324	0.210	0.377	0.285	0.136

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

Table C3: AI Pricing and Firm Performance: Long-differences by Industry, Part III

	Finance, Insurance, & Real Estate				Professional & Business Services			
	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.128	-0.620	-1.770	3.593***	-2.242*	-2.413**	-1.411	0.708***
	(1.904)	(1.634)	(2.089)	(1.308)	(1.262)	(0.942)	(1.524)	(0.267)
Share of AI	-9.392***	-6.597**	-10.923***	6.007***	1.499	-1.243	-0.389	1.297***
	(3.303)	(2.827)	(3.627)	(2.269)	(2.012)	(1.439)	(2.430)	(0.426)
Share of Pricing	0.008	0.364	0.057	-0.138	-6.751**	1.159	0.264	1.640***
	(0.214)	(0.393)	(0.235)	(0.147)	(2.921)	(2.095)	(3.527)	(0.618)
Log Sales	-0.102***	-0.037**	-0.127***	-0.037***	-0.106**	-0.052	-0.084*	0.023**
	(0.018)	(0.015)	(0.020)	(0.012)	(0.042)	(0.035)	(0.051)	(0.009)
Log TFP	-0.065	0.092**	-0.064	-0.199***	0.185*	0.381***	0.025	-0.023
	(0.046)	(0.040)	(0.050)	(0.032)	(0.103)	(0.081)	(0.125)	(0.022)
Log Age	-0.135***	-0.169***	-0.075*	0.004	-0.049	-0.043	-0.029	0.039**
	(0.039)	(0.034)	(0.043)	(0.027)	(0.074)	(0.056)	(0.090)	(0.016)
Tobin's Q	-0.085	-0.011	0.347***	-0.041	0.108	0.365***	0.534***	-0.000
	(0.094)	(0.086)	(0.103)	(0.064)	(0.135)	(0.106)	(0.164)	(0.029)
Cash/Assets	0.358	0.700***	-0.222	0.422**	0.280	-0.265	-0.629	-0.198**
	(0.269)	(0.249)	(0.295)	(0.185)	(0.440)	(0.324)	(0.532)	(0.093)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	620	605	623	620	148	128	148	148
adj. R^2	0.111	0.089	0.134	0.127	0.129	0.299	0.035	0.243

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

Table C4: AI Pricing and Firm Performance: Long-differences by Industry, Part IV

	Education, Healthcare, & Entertainment				All Other Industries			
	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	107.885***	90.235***	84.564***	-6.403	-0.592**	-0.523	-0.628**	-0.101
	(13.256)	(17.070)	(11.908)	(4.360)	(0.299)	(0.321)	(0.302)	(0.092)
Share of AI	186.132	440.836	106.454	-10.169	-6.027	-9.388	-8.468	-0.297
	(209.905)	(270.308)	(188.568)	(69.042)	(11.149)	(11.970)	(11.284)	(3.423)
Share of Pricing	-2.942	-7.548	-2.364	0.114	1.361	1.804	-0.313	-0.366
	(5.464)	(7.036)	(4.908)	(1.797)	(1.141)	(1.230)	(1.155)	(0.350)
Log Sales	-0.307***	-0.401***	-0.322***	0.007	-0.226***	-0.175***	-0.111***	0.054***
	(0.033)	(0.043)	(0.030)	(0.011)	(0.026)	(0.028)	(0.026)	(0.008)
Log TFP	0.031	0.125	0.064	-0.011	0.140***	0.074	-0.015	-0.029**
	(0.059)	(0.076)	(0.053)	(0.019)	(0.042)	(0.046)	(0.043)	(0.013)
Log Age	0.442***	0.429***	0.605***	0.052**	-0.101***	-0.018	-0.109***	0.005
	(0.062)	(0.080)	(0.056)	(0.020)	(0.034)	(0.037)	(0.034)	(0.010)
Tobin's Q	0.848***	0.663***	0.999***	-0.217***	0.196**	0.246***	0.660***	-0.095***
	(0.103)	(0.133)	(0.093)	(0.034)	(0.085)	(0.092)	(0.086)	(0.026)
Cash/Assets	-1.670***	-2.650***	-0.947***	0.115	0.380	1.027***	0.061	0.223**
	(0.386)	(0.497)	(0.347)	(0.127)	(0.338)	(0.369)	(0.342)	(0.104)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	111	111	111	111	510	494	510	510
adj. R^2	0.657	0.557	0.740	0.365	0.318	0.301	0.306	0.168

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

C.1.2 Excluding Largest Firms by Top 1%, 5%, or 10%

We examine the long-difference regressions while dropping the largest leading firms in sales by the top 1%, 5%, or 10%. The results show that the largest firms do not solely drive the firm performance effects of AI pricing, even dropping all firms in the top 10%.

Table C5: AI Pricing and Firm Performance: Long-differences, Drop Top 1%

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.247***	0.849***	1.075***	0.575**	1.200***	0.800**	0.266	0.291**
	(0.334)	(0.293)	(0.288)	(0.254)	(0.346)	(0.313)	(0.168)	(0.123)
Share of AI		-0.015		-0.325		-0.231		-0.645**
		(0.666)		(0.573)		(0.711)		(0.279)
Share of Pricing		0.256		0.684***		0.327		-0.036
		(0.189)		(0.244)		(0.202)		(0.079)
Log Sales		-0.095***		-0.099***		-0.115***		0.004
		(0.009)		(0.008)		(0.010)		(0.004)
Log TFP		-0.015		0.117***		-0.017		-0.086***
		(0.020)		(0.018)		(0.022)		(0.008)
Log Age		-0.118***		-0.116***		-0.111***		0.003
		(0.016)		(0.014)		(0.017)		(0.007)
Tobin's Q		0.443***		0.360***		0.694***		-0.031**
		(0.036)		(0.032)		(0.038)		(0.015)
Cash/Assets		-0.021		0.143		-0.313***		0.188***
		(0.104)		(0.096)		(0.111)		(0.044)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3936	3516	3602	3229	3947	3520	3936	3516
adj. R^2	0.065	0.183	0.087	0.221	0.048	0.200	0.018	0.054

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

Table C6: AI Pricing and Firm Performance: Long-differences, Drop Top 5%

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.105***	0.680**	0.841***	0.340	1.077***	0.644**	0.240	0.237*
	(0.341)	(0.299)	(0.290)	(0.257)	(0.353)	(0.320)	(0.175)	(0.126)
Share of AI		-0.142		-0.457		-0.337		-0.628**
		(0.674)		(0.573)		(0.720)		(0.285)
Share of Pricing		0.213		0.622**		0.280		-0.041
		(0.192)		(0.246)		(0.205)		(0.081)
Log Sales		-0.105***		-0.106***		-0.117***		0.002
		(0.011)		(0.010)		(0.011)		(0.005)
Log TFP		-0.023		0.117***		-0.032		-0.086***
		(0.021)		(0.019)		(0.023)		(0.009)
Log Age		-0.116***		-0.108***		-0.113***		0.002
		(0.017)		(0.015)		(0.018)		(0.007)
Tobin's Q		0.450***		0.348***		0.700***		-0.035**
		(0.037)		(0.033)		(0.039)		(0.016)
Cash/Assets		-0.103		0.069		-0.401***		0.173***
		(0.108)		(0.099)		(0.116)		(0.046)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3675	3276	3354	2994	3686	3280	3675	3276
adj. R^2	0.069	0.178	0.088	0.205	0.054	0.192	0.021	0.056

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

Table C7: AI Pricing and Firm Performance: Long-differences, Drop Top 10%

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.184***	0.695**	0.973***	0.416	1.310***	0.811**	0.351*	0.341***
	(0.361)	(0.318)	(0.301)	(0.265)	(0.372)	(0.339)	(0.185)	(0.131)
Share of AI		-0.093		-0.400		-0.309		-0.648**
		(0.692)		(0.572)		(0.739)		(0.285)
Share of Pricing		0.225		0.684***		0.301		-0.053
		(0.200)		(0.253)		(0.213)		(0.082)
Log Sales		-0.089***		-0.087***		-0.106***		0.008
		(0.013)		(0.011)		(0.013)		(0.005)
Log TFP		-0.030		0.131***		-0.026		-0.087***
		(0.023)		(0.020)		(0.024)		(0.009)
Log Age		-0.138***		-0.132***		-0.130***		-0.010
		(0.018)		(0.016)		(0.019)		(0.007)
Tobin's Q		0.442***		0.322***		0.693***		-0.056***
		(0.039)		(0.034)		(0.041)		(0.016)
Cash/Assets		-0.095		0.078		-0.432***		0.252***
		(0.113)		(0.101)		(0.121)		(0.047)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3345	2975	3032	2701	3356	2979	3345	2975
adj. R^2	0.057	0.158	0.066	0.176	0.042	0.173	0.023	0.061

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

C.1.3 Controlling for Changes in AI Share and Pricing Share

Table C8: AI Pricing and Firm Performance: Long-differences, Controlling Other Changes

	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	0.833^{***}	0.541^{**}	0.785^{**}	0.272^{**}	0.857^{***}	0.562^{**}	0.808^{***}	0.283^{**}
	(0.290)	(0.252)	(0.309)	(0.121)	(0.291)	(0.252)	(0.309)	(0.121)
$\Delta AIS_{j,[2010,2023]}$	2.257^{***}	1.830^{***}	2.028^{***}	0.967^{***}				
	(0.706)	(0.612)	(0.752)	(0.295)				
$\Delta PS_{j,[2010,2023]}$					-0.163	-0.721	-0.593	-0.237
					(0.629)	(0.576)	(0.669)	(0.263)
Share of AI	-0.904	-1.037^{*}	-1.023	-1.008^{***}	-0.032	-0.348	-0.250	-0.639^{**}
	(0.717)	(0.617)	(0.764)	(0.299)	(0.664)	(0.571)	(0.707)	(0.277)
Share of Pricing	0.252	0.715^{***}	0.321	-0.035	0.265	0.839^{***}	0.367^{*}	-0.016
	(0.188)	(0.242)	(0.200)	(0.079)	(0.195)	(0.263)	(0.207)	(0.081)
Log Sales	-0.091^{***}	-0.100^{***}	-0.109^{***}	0.004	-0.088^{***}	-0.097^{***}	-0.106^{***}	0.005
	(0.009)	(0.008)	(0.009)	(0.004)	(0.009)	(0.008)	(0.009)	(0.004)
Log TFP	-0.022	0.112^{***}	-0.020	-0.088^{***}	-0.014	0.120^{***}	-0.012	-0.085^{***}
	(0.020)	(0.018)	(0.022)	(0.008)	(0.020)	(0.018)	(0.021)	(0.008)
Log Age	-0.115^{***}	-0.112^{***}	-0.108^{***}	0.004	-0.117^{***}	-0.114^{***}	-0.109^{***}	0.003
	(0.016)	(0.014)	(0.017)	(0.007)	(0.016)	(0.014)	(0.017)	(0.007)
Tobin's Q	0.432^{***}	0.356^{***}	0.680^{***}	-0.033^{**}	0.436^{***}	0.360^{***}	0.684^{***}	-0.032^{**}
	(0.035)	(0.032)	(0.038)	(0.015)	(0.035)	(0.032)	(0.038)	(0.015)
Cash/Assets	-0.047	0.128	-0.336^{***}	0.163^{***}	0.004	0.175^{*}	-0.288^{***}	0.185^{***}
	(0.104)	(0.096)	(0.111)	(0.044)	(0.103)	(0.095)	(0.110)	(0.043)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3583	3293	3587	3583	3583	3293	3587	3583
adj. R^2	0.186	0.230	0.202	0.056	0.183	0.228	0.200	0.054

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \gamma\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. And $\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\}$ measures the changes in AI share and Pricing share in the same fashion. Both the changes in AI share and Pricing share are orthogonal to $\Delta APS_{j,[t1,t2]}$, so AI pricing jobs are not picked up in either of the measures. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

Table C9: AI Pricing and Firm Performance: Long-differences, Controlling Both Changes

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.070^{***}	0.833^{***}	0.860^{***}	0.544^{**}	1.017^{***}	0.786^{**}	0.245	0.272^{**}
	(0.332)	(0.290)	(0.286)	(0.252)	(0.344)	(0.309)	(0.167)	(0.121)
$\Delta AIS_{j,[2010,2023]}$	3.099^{***}	2.256^{***}	3.333^{***}	1.826^{***}	3.044^{***}	2.026^{***}	0.416	0.966^{***}
	(0.721)	(0.706)	(0.620)	(0.612)	(0.745)	(0.752)	(0.362)	(0.295)
$\Delta PS_{j,[2010,2023]}$	-1.058	-0.157	-0.589	-0.711	-1.497^{**}	-0.587	-0.534	-0.234
	(0.670)	(0.628)	(0.581)	(0.575)	(0.692)	(0.669)	(0.336)	(0.262)
Share of AI		-0.907		-1.051^{*}		-1.036		-1.013^{***}
		(0.717)		(0.617)		(0.764)		(0.299)
Share of Pricing		0.265		0.840^{***}		0.367^{*}		-0.016
		(0.194)		(0.263)		(0.207)		(0.081)
Log Sales		-0.091^{***}		-0.100^{***}		-0.109^{***}		0.004
		(0.009)		(0.008)		(0.009)		(0.004)
Log TFP		-0.021		0.113^{***}		-0.018		-0.088^{***}
		(0.020)		(0.018)		(0.022)		(0.008)
Log Age		-0.115^{***}		-0.112^{***}		-0.107^{***}		0.004
		(0.016)		(0.014)		(0.017)		(0.007)
Tobin's Q		0.432^{***}		0.357^{***}		0.680^{***}		-0.033^{**}
		(0.035)		(0.032)		(0.038)		(0.015)
Cash/Assets		-0.046		0.131		-0.333^{***}		0.164^{***}
		(0.104)		(0.096)		(0.111)		(0.044)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4014	3583	3677	3293	4025	3587	4014	3583
adj. R^2	0.068	0.185	0.093	0.230	0.054	0.202	0.019	0.056

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \gamma\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_i$, where $\Delta APS_{j,[t1,t2]}$ is the difference between the AI pricing share measure $APS_{j,t2}$ and $APS_{j,t1}$, in which $t1$ includes four quarters in 2010 and $t2$ includes the corresponding four quarters in 2023. And $\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\}$ measures the changes in AI share and Pricing share in the same fashion. Both the changes in AI share and Pricing share are orthogonal to $\Delta APS_{j,[t1,t2]}$, so AI pricing jobs are not picked up in either of the measures. We omit 2024Q1 for potential seasonality. $Z_{i,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, size, age, productivity, and other balance sheet characteristics in $t1$. Finally, γ_s in the two-digit NAICS industry fixed effect.

C.2 Additional Firm Performances Results from Monetary Policy Shocks

We provide robustness checks to exclude either (1) financial and utility firms because of the concern that these firms may naturally react differently to monetary policy shocks due to their production process or (2) information technology firms because of the concern that these firms may react differently to monetary policy shocks due to their intensive usage of AI.

C.2.1 Excluding Financial and Utility Firms

Table C10: Response of Stock Return to Monetary Shocks: Interaction with Controls

	Excluding Financial and Utility Firms								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MP_e \times APS_{j,t-1}$	4.881^{*}	5.354^{**}	5.391^{**}	5.377^{**}	5.794^{**}	5.362^{**}	5.725^{**}	5.460^{**}	5.177^{*}
	(2.704)	(2.694)	(2.695)	(2.695)	(2.695)	(2.694)	(2.699)	(2.694)	(2.716)
$MP_e \times FPA_s$	0.486^{***}	0.470^{***}	0.491^{***}	0.469^{***}	0.426^{***}	0.430^{***}	0.443^{***}	0.406^{***}	0.406^{***}
	(0.116)	(0.116)	(0.122)	(0.116)	(0.117)	(0.118)	(0.118)	(0.120)	(0.127)
$MP_e \times$ Share of AI	10.855^{**}								13.641^{***}
	(4.608)								(4.703)
$MP_e \times$ Share of Pricing		-2.934							-2.798
		(2.108)							(2.113)
$MP_e \times$ Log Sales			-0.040						0.040
			(0.083)						(0.107)
$MP_e \times$ Log Age				-0.133					-0.158
				(0.170)					(0.182)
$MP_e \times$ Log TFP					-0.628^{***}				-0.701^{***}
					(0.164)				(0.252)
$MP_e \times$ Log Tobin's Q						-0.598^{**}			-0.235
						(0.253)			(0.311)
$MP_e \times$ Cash/Asset							-1.351^{*}		-0.889
							(0.775)		(1.016)
$MP_e \times$ Log Markup								-0.556^{**}	0.266
								(0.235)	(0.345)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	24432	24432	24432	24432	24432	24432	24432	24432	24432
adj. R^2	0.175	0.175	0.175	0.175	0.176	0.175	0.175	0.175	0.176

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Empirical specification: $R_{j,e} = \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times X_{j,t-1} + \beta_3 X_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 MP_e \times Z_{j,t-1} + \gamma_j + \gamma_e + \epsilon_{je}$, where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e is our monetary shocks, $X_{j,t-1}$ denotes the variables of interest (demeaned if are continuous), including firm-level lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$, firm-level lagged AI pricing adoption share $APS_{j,t-1}$, and industry-level frequency of price adjustment FPA_s, where t denotes a quarter and s denotes a NAICS 6-digit industry. We also include the same group of firm-level controls as in the long-differences regressions, including (1) lagged firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash/asset); and (2) lagged firm-level share of AI workers and share of pricing workers which we orthogonal to the firm-level lagged AI pricing adoption share $APS_{j,t-1}$. We also include lagged markup as an additional control. Finally, we include firm fixed effect and event fixed effect. Our identification operates through changes in the discounted value of profits from changes in future demand and costs that are immediately incorporated in stock returns following the monetary policy surprises.

C.2.2 Excluding Information Technology Firms

Table C11: Response of Stock Return to Monetary Shocks: Interaction with Controls

	Excluding Information Technology Firms								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MP_e \times APS_{j,t-1}$	4.905*	5.370**	5.408**	5.385**	5.829**	5.378**	5.742**	5.482**	5.210*
	(2.702)	(2.693)	(2.694)	(2.693)	(2.694)	(2.692)	(2.697)	(2.692)	(2.714)
$MP_e \times FPA_s$	0.483***	0.467***	0.488***	0.465***	0.423***	0.425***	0.438***	0.403***	0.397***
	(0.117)	(0.116)	(0.122)	(0.117)	(0.117)	(0.118)	(0.118)	(0.120)	(0.127)
MP_e × Share of AI	10.738**								13.538***
	(4.607)								(4.702)
MP_e × Share of Pricing		-2.915							-2.778
		(2.107)							(2.113)
MP_e × Log Sales			-0.040						0.042
			(0.083)						(0.107)
MP_e × Log Age				-0.159					-0.193
				(0.172)					(0.184)
MP_e × Log TFP					-0.629***				-0.697***
					(0.165)				(0.253)
MP_e × Log Tobin's Q						-0.603**			-0.236
						(0.254)			(0.312)
MP_e × Cash/Asset							-1.363*		-0.921
							(0.777)		(1.019)
MP_e × Log Markup								-0.559**	0.257
								(0.236)	(0.345)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	24240	24240	24240	24240	24240	24240	24240	24240	24240
adj. R^2	0.176	0.176	0.176	0.176	0.177	0.176	0.176	0.176	0.177

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Empirical specification: $R_{j,e} = \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times X_{j,t-1} + \beta_3 X_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 MP_e \times Z_{j,t-1} + \gamma_j + \gamma_e + \epsilon_{je}$, where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e is our monetary shocks, $X_{j,t-1}$ denotes the variables of interest (demeaned if are continuous), including firm-level lagged AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$, firm-level lagged AI pricing adoption share $APS_{j,t-1}$, and industry-level frequency of price adjustment FPA_s, where t denotes a quarter and s denotes a NAICS 6-digit industry. We also include the same group of firm-level controls as in the long-differences regressions, including (1) lagged firm-level characteristics that predict changes in AI pricing adoption in Section 3 (log sales, log TFP, firm age, Tobin's Q, and cash/asset); and (2) lagged firm-level share of AI workers and share of pricing workers which we orthogonal to the firm-level lagged AI pricing adoption share $APS_{j,t-1}$. We also include lagged markup as an additional control. Finally, we include firm fixed effect and event fixed effect. Our identification operates through changes in the discounted value of profits from changes in future demand and costs that are immediately incorporated in stock returns following the monetary policy surprises.

D Supplements to the Model

D.1 Additional Proofs

D.1.1 Proof of Lemma 1

Proof. The conditional maximization problem (5) implies the first order condition for each j:

$$p_j - \kappa = \frac{\mathbb{E}\left[d_j(p_j)|\Omega\right]}{\mathbb{E}\left[d_j'(p_j)|\Omega\right]}$$

which in terms of the linear demand function (4) is

$$p_j - \kappa = \frac{\mathbb{E}\left[z_j|\Omega\right] - \eta p_j}{\eta}$$

Inverting to find p_j gives the solution. ■

D.1.2 Proof of Lemma 2

Proof. The linear demand function (4) implies that for each individual j, the expected profit is

$$\mathbb{E}\left[\pi_j(p_j)\right] = \mathbb{E}\left[(p_j - \kappa)(z_j - \eta p_j)\right]$$

and Lemma 1 implies

$$\mathbb{E}\left[\pi_j(p_j)\right] = \mathbb{E}\left[\left(\frac{\mathbb{E}\left[z_j|\Omega\right]}{2\eta} - \frac{\kappa}{2}\right)\left(z_j - \frac{\mathbb{E}\left[z_j|\Omega\right]}{2} - \frac{\eta\kappa}{2}\right)\right]$$

$$= \frac{1}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] - \eta\kappa\right)\left(z_j - \mathbb{E}\left[z_j|\Omega\right] + z_j - \eta\kappa\right)\right] = \frac{1}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] - \eta\kappa\right)\left(z_j - \eta\kappa\right)\right]$$

because the forecast error $z_j - \mathbb{E}\left[z_j|\Omega\right]$ must be statistically independent of $\mathbb{E}\left[z_j|\Omega\right] - \eta\kappa$. Then, take conditional expectations

$$= \frac{1}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] - \eta\kappa\right)\left(\mathbb{E}\left[z_j|\Omega\right] - \eta\kappa\right)\right] = \frac{1}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] - \bar{z} + \bar{z} - \eta\kappa\right)\left(\mathbb{E}\left[z_j|\Omega\right] - \bar{z} + \bar{z} - \eta\kappa\right)\right]$$

which introduces the unconditional expectation is $\overline{z} = \mathbb{E}\left[z_j\right]$. As before, the forecast update $\mathbb{E}\left[z_j|\Omega\right] - \overline{z}$ must be statistically independent of $\overline{z} - \eta\kappa$:

$$= \frac{1}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] - \overline{z}\right)^2 (\overline{z} - \eta\kappa)^2\right] = \frac{(\overline{z} - \eta\kappa)^2}{4\eta}\mathbb{V}\left[\mathbb{E}\left[z_j|\Omega\right]\right]$$

There is a measure μ of individuals, so integrating over individuals gives

$$\mathbb{E}\left[\int_{j\in\mathcal{J}} \pi_j(p_j)dj\right] = \int_{j\in\mathcal{J}} \frac{(\overline{z} - \eta\kappa)^2}{4\eta}\mathbb{V}\left[\mathbb{E}\left[z_j|\Omega\right]\right] dj = \mu\frac{(\overline{z} - \eta\kappa)^2}{4\eta}\mathbb{V}\left[\mathbb{E}\left[z_j|\Omega\right]\right]$$

and substituting with the j-invariant notation $\nu R(N) = \mathbb{V}\left[\mathbb{E}\left[z_j|\Omega\right]\right]$ proves the proposition. ■

D.1.3 Proof of Lemma 3

Proof. If firms prefer to adopt AI pricing (condition (13)), all of its first order conditions hold.

First we find the implied AI pricing inputs. $R'(N) = \frac{\rho}{\nu}$, so the first order condition (7) becomes

$$w = \mu\Phi\rho\beta L_b^{\beta-1}$$

$$\implies L_b = \left(\frac{\mu\Phi\rho\beta}{w}\right)^{\frac{1}{1-\beta}} \tag{15}$$

where $\Phi = \frac{(\overline{z}-\eta\kappa)^2}{4\eta}$. Equation (11) becomes

$$\frac{w}{q} = \frac{F_a(L_a, L_b, C)}{F_c(L_a, L_b, C)} = \frac{\alpha A^\alpha L_a^{\alpha-1} C^\gamma}{\gamma A^\alpha L_a^\alpha C^{\gamma-1}}$$

$$\implies \frac{C}{L_a} = \frac{w}{q}\frac{\gamma}{\alpha} \tag{16}$$

and equation (10) becomes

$$F_a(L_a, L_b, C) = F_b(L_a, L_b, C)$$

$$\alpha A^\alpha L_a^{\alpha-1} C^\gamma = \beta L_b^{\beta-1} \tag{17}$$

Plugging in equations (15) and (16) gives

$$\alpha A^\alpha (\frac{w}{q}\frac{\gamma}{\alpha})^\gamma L_a^{\alpha+\gamma-1} = \frac{w}{\mu\Phi\rho}$$

$$\implies L_a = \left(\alpha^{1-\gamma} w^{\gamma-1} A^\alpha (\frac{\gamma}{q})^\gamma \mu\Phi\rho\right)^{\frac{1}{1-(\alpha+\gamma)}} \tag{18}$$

Equation (16) says computing is given by $C = \frac{\gamma w}{\alpha q} L_a$, so the condition in equation (13) becomes:

$$\mu \Phi \rho A^{\alpha} (\frac{w}{q})^{\gamma} L_a^{\alpha+\gamma} \geq (1 + \frac{\gamma}{\alpha}) w L_a + \chi$$

Equation (18) gives the solution for L_a. Plug it into the condition in equation (13):

$$\mu \Phi \rho A^{\alpha} (\frac{w}{q})^{\gamma} \left(\mu \Phi \rho \alpha^{1-\gamma} w^{\gamma-1} A^{\alpha} (\frac{\gamma}{q})^{\gamma} \right)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}} \geq (1 + \frac{\gamma}{\alpha}) w \left(\mu \Phi \rho \alpha^{1-\gamma} w^{\gamma-1} A^{\alpha} (\frac{\gamma}{q})^{\gamma} \right)^{\frac{1}{1-(\alpha+\gamma)}} + \chi$$

which simplifies to

$$(\mu \Phi \rho A^{\alpha})^{\frac{1}{1-(\alpha+\gamma)}} \, q^{-\frac{\gamma}{1-(\alpha+\gamma)}} \, w^{-\frac{\alpha}{1-(\alpha+\gamma)}} \left(\alpha^{1-\gamma} \gamma^{\gamma} \right)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}} (1 - (\alpha + \gamma) \alpha^{-\gamma} \gamma^{\gamma}) \geq \chi$$

The firm is willing to use AI pricing whenever this condition holds, so rearranging gives the smallest μ such that they will do so:

$$\underline{\mu}(q) = \frac{q^{\gamma} w^{\alpha}}{\Phi \rho A^{\alpha} (\alpha^{1-\gamma} \gamma^{\gamma})^{\alpha+\gamma}} \left(\frac{\chi}{1 - (\alpha + \gamma) \alpha^{-\gamma} \gamma^{\gamma}} \right)^{1-(\alpha+\gamma)}$$

The assumption that $1 > (\alpha + \gamma) \alpha^{-\gamma} \gamma^{\gamma}$ ensures that this function is increasing. ■

D.1.4 Proof of Lemma 4

Proof. Equation 18 gives the pricing labor input as

$$L_a = \left(\alpha^{1-\gamma} w^{\gamma-1} A^{\alpha} (\frac{\gamma}{q})^{\gamma} \mu \Phi \rho \right)^{\frac{1}{1-(\alpha+\gamma)}}$$

$1 - (\alpha + \gamma) > 0$ by assumption, so L_a is decreasing in q. L_b is strictly positive and does not depend on q or A, so the AI share $\frac{L_a}{L_a + L_b}$ is also strictly decreasing in q.

■

D.1.5 Proof of Lemma 5

Proof. The share $\frac{L_a}{L_a + L_b}$ is increasing in μ if and only if the ratio $\frac{L_a}{L_b}$ is increasing. Conditional on adopting AI pricing, the ratio $\frac{L_a}{L_b}$ is given from equations (15) and (18) by

$$\frac{L_a}{L_b} = \alpha^{\frac{1-\gamma}{1-(\alpha+\gamma)}} \gamma^{\frac{\gamma}{1-(\alpha+\gamma)}} A^{\frac{\alpha}{1-(\alpha+\gamma)}} q^{\frac{-\gamma}{1-(\alpha+\gamma)}} w^{\frac{1}{1-\beta} - \frac{1-\gamma}{1-(\alpha+\gamma)}} (\mu \Phi \rho)^{\frac{1}{1-(\alpha+\gamma)} - \frac{1}{1-\beta}} \tag{19}$$

which is increasing in μ if and only if $\frac{1}{1-(\alpha+\gamma)} - \frac{1}{1-\beta} \geq 0$. Denominators $1-(\alpha+\gamma)$ and $1-\beta$ are both positive, so the necessary and sufficient condition is equivalent to $\beta < \alpha + \gamma$. ■

D.1.6 Proof of Lemma 6

Proof. Using the first order condition (16), the production function for observing components (12) becomes

$$N = L_b^{\beta} + A^{\alpha}\left(\frac{w}{q}\frac{\gamma}{\alpha}\right)^{\gamma} L_a^{\alpha+\gamma}$$

and the labor choices (15) and (18) imply

$$N = \left(\frac{\mu\Phi\rho\beta}{w}\right)^{\frac{\beta}{1-\beta}} + A^{\alpha}\left(\frac{w}{q}\frac{\gamma}{\alpha}\right)^{\gamma}\left(\alpha^{1-\gamma}w^{\gamma-1}A^{\alpha}(\frac{\gamma}{q})^{\gamma}\mu\Phi\rho\right)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}} \tag{20}$$

The right-hand side is increasing in μ and decreasing in q, so N must be as well for $N < \frac{\nu}{\rho}$. ■

D.1.7 Proof of Lemma 7

Proof. The firm's revenue y is given by

$$y = \int_{j\in\mathcal{J}} p_j d_j(p_j) dj$$

By Lemma 1, the optimal price is $p_j = \frac{\mathbb{E}[z_j|\Omega]}{2\eta} + \frac{\kappa}{2}$

$$= \int_{j\in\mathcal{J}}\left(\frac{\mathbb{E}\left[z_j|\Omega\right]}{2\eta} + \frac{\kappa}{2}\right)\left(z_j - \frac{\mathbb{E}\left[z_j|\Omega\right]}{2} - \frac{\eta\kappa}{2}\right)dj$$

which we can rewrite using unconditional expectations:

$$= \frac{\mu}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] + \eta\kappa\right)\left(z_j - \mathbb{E}\left[z_j|\Omega\right] + z_j - \eta\kappa\right)\right]$$

$$= \frac{\mu}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] + \eta\kappa\right)\left(z_j - \eta\kappa\right)\right] = \frac{\mu}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] + \eta\kappa\right)\left(\mathbb{E}\left[z_j|\Omega\right] - \eta\kappa\right)\right]$$

$$= \frac{\mu}{4\eta}\mathbb{E}\left[\left(\mathbb{E}\left[z_j|\Omega\right] - \bar{z} + \bar{z} + \eta\kappa\right)\left(\mathbb{E}\left[z_j|\Omega\right] - \bar{z} + \bar{z} - \eta\kappa\right)\right] = \frac{\mu}{4\eta}\left(\mathbb{V}\left[\mathbb{E}\left[z_j|\Omega\right]\right] + (\bar{z} + \eta\kappa)(\bar{z} - \eta\kappa)\right)$$

$$= \mu\frac{\nu R(N) + \bar{z}^2 - \eta^2\kappa^2}{4\eta}$$

$\eta > 0$, $R(N)$ is increasing in N, and by Lemma 6, N is increasing in μ and decreasing in q. ■

D.1.8 Proof of Lemma 8

Proof. Firms produce with constant marginal cost κ, so the firm's average markup is given by

$$m = \frac{y}{\kappa \int_{j \in \mathcal{J}} d_j(p_j) dj} - 1$$

By Lemma 1, the optimal price is $p_j = \frac{\mathbb{E}[z_j|\Omega]}{2\eta} + \frac{\kappa}{2}$, so the demand function implies

$$= \frac{y}{\kappa \int_{j \in \mathcal{J}} \left(z_j - \frac{\mathbb{E}[z_j|\Omega]}{2} - \frac{\eta\kappa}{2} \right) dj} - 1$$

which we can rewrite using unconditional expectations:

$$= \frac{y}{\kappa \mu \mathbb{E}\left[z_j - \frac{\mathbb{E}[z_j|\Omega]}{2} - \frac{\eta\kappa}{2} \right]} - 1 = \frac{y}{\kappa \mu \left(\frac{\bar{z}}{2} - \frac{\eta\kappa}{2} \right)} - 1 \tag{21}$$

Then substitute for revenue with equation (14):

$$m = \frac{\nu R(N) + \bar{z}^2 - \eta^2 \kappa^2}{4\eta\kappa \left(\frac{\bar{z}}{2} - \frac{\eta\kappa}{2} \right)} - 1$$

By Lemma 6, $R(N)$ is increasing in μ and decreasing in q, and $\frac{\bar{z}}{2} - \frac{\eta\kappa}{2}$ is necessarily positive. ■

D.1.9 Proof of Lemma 9

Proof. *Result (1)*: The definition (6) implies Φ is increasing in $\bar{z}$ because we assumed $\bar{z} > \eta\kappa$ so that firms make positive profits. L_b is increasing in Φ by equation (15), L_a is increasing in Φ by equation (18), and C is increasing in L_a by equation (16).

Result (2): The labor ratio $\frac{L_a}{L_b}$ is increasing in Φ if and only if $\beta < \alpha + \gamma$ by equation (19), and the share $\frac{L_a}{L_a + L_b}$ is increasing in the ratio $\frac{L_a}{L_b}$.

Result (3): Factor observation N is increasing $\bar{z}$ by *Result (1)*. Per equation (14), revenue y is increasing in both N and $\bar{z}$.

Result (4): Gross profits π (i.e. before accounting for pricing costs) are

$$\pi = y - \kappa \int_{j \in \mathcal{J}} d_j(p_j) dj$$

which simplifies by equations (14) and (21):

$$= \mu \frac{\nu R(N) + \overline{z}^2 - \eta^2\kappa^2}{4\eta} - \kappa\mu\left(\frac{\overline{z}}{2} - \frac{\eta\kappa}{2}\right) = \frac{\mu}{2\eta}\left(\rho N + (\bar{z} - \eta\kappa)^2\right)$$

Again, N is increasing in $\bar{z}$ by *Result (1)*, and $(\bar{z} - \eta\kappa)^2$ is increasing in $\bar{z}$ because we assumed $\bar{z} > \eta\kappa$.

■

D.1.10 Proof of Proposition 5

Proof. Express a firm's gross profits as a function of demand $\bar{z}$ and market size μ:

$$\pi(\bar{z}, \mu) = \frac{\mu}{2\eta}\left(\rho N(\bar{z}, \mu) + (\bar{z} - \eta\kappa)^2\right)$$

where the function $N(\bar{z}, \mu)$ is given by equation (20).

Demand $\bar{z}$ affects gross profits by

$$\frac{\partial \pi(\bar{z}, \mu)}{\partial \bar{z}} = \frac{\mu\rho}{2\eta}\frac{\partial N(\bar{z}, \mu)}{\partial \bar{z}} + \frac{\mu}{\eta}(\bar{z} - \eta\kappa)$$

Firms differ by their market size μ. The effect of market size on the derivative is

$$\frac{\partial^2 \pi(\bar{z}, \mu)}{\partial \mu \partial \bar{z}} = \frac{\rho}{2\eta}\frac{\partial N(\bar{z}, \mu)}{\partial \bar{z}} + \frac{\mu\rho}{2\eta}\frac{\partial^2 N(\bar{z}, \mu)}{\partial \mu \partial \bar{z}} + \frac{\bar{z} - \eta\kappa}{\eta} \tag{22}$$

The partial derivatives are

$$\frac{\partial N(\bar{z}, \mu)}{\partial \bar{z}} = \frac{\partial N(\bar{z}, \mu)}{\partial \Phi}\frac{\partial \Phi}{\partial \bar{z}}$$

$$= \left(\left(\frac{\beta}{1-\beta}\right)\left(\frac{\mu\rho\beta}{w}\right)^{\frac{\beta}{1-\beta}} \Phi^{\frac{\beta}{1-\beta}-1} + \right.$$

$$\left. \ldots \left(\frac{\alpha+\gamma}{1-(\alpha+\gamma)}\right) A^{\alpha}\left(\frac{w}{q}\frac{\gamma}{\alpha}\right)^{\gamma}\left(\alpha^{1-\gamma} w^{\gamma-1} A^{\alpha} (\frac{\gamma}{q})^{\gamma} \mu\rho\right)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}} \Phi^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}-1}\right)\frac{\partial \Phi}{\partial \bar{z}}$$

and

$$\frac{\partial^2 N(\bar{z},\mu)}{\partial\mu\partial\bar{z}} = \Bigg(\left(\frac{\beta}{1-\beta}\right)^2 \left(\frac{\rho\beta}{w}\right)^{\frac{\beta}{1-\beta}} (\mu\Phi)^{\frac{\beta}{1-\beta}-1} +$$

$$\dots \left(\frac{\alpha+\gamma}{1-(\alpha+\gamma)}\right)^2 A^\alpha \left(\frac{w}{q}\frac{\gamma}{\alpha}\right)^\gamma \left(\alpha^{1-\gamma} w^{\gamma-1} A^\alpha (\frac{\gamma}{q})^\gamma \rho\right)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}} (\mu\Phi)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}-1} \Bigg) \frac{\partial\Phi}{\partial\bar{z}}$$

By assumption $\bar{z} > \eta\kappa$, so per the definition (6) $\frac{\partial\Phi}{\partial\bar{z}} > 0$. Thus, all terms in equation (22) are positive. ■

D.2 Time-Series and Cross-Section Data for the Model

Table D1: Time Series of AI pricing adoption

Year	AI pricing Share	Adoption Rate	AI Computing Cost
2010	0.12%	0.22%	\$0.441
2011	0.06%	0.13%	\$0.374
2012	0.10%	0.27%	\$0.308
2013	0.14%	0.38%	\$0.241
2014	0.25%	0.46%	\$0.185
2015	0.25%	0.50%	\$0.192
2016	0.48%	0.85%	\$0.086
2017	0.63%	1.66%	\$0.100
2018	1.00%	1.89%	\$0.090
2019	1.33%	2.35%	\$0.064
2020	1.34%	2.32%	\$0.039
2021	1.62%	4.62%	\$0.036
2022	1.56%	3.51%	\$0.033
2023	1.36%	3.44%	\$0.017

Notes: The data source for the AI Pricing is our Lightcast, and the data source for the AI computing cost is Epoch AI.

Time Series of the AI Computing Costs Our time-series data for the AI computing costs q in the model is calculated using the microdata of the cost efficiency of major machine-learning (ML) GPUs from a real-time database "Data on ML GPUs" updated by Epoch AI. The database keeps tracking the release dates, release prices, and performance measures of all the major ML GPUs since 2008. Most of these are Nvidia GPUs, mainly in the GeForce series. Others include specialized GPUs such as Nvidia Tesla GPUs. Since different GPUs could have different focuses, we focused on the GeForce series to calculate cost efficiency.

We first deflate the release prices by the Consumer Price Index with the 2023 price normalized to 1 dollar. We then choose the single precision giga (1 billion) floating-point operations per second (GFLOPs) as our measure of performance. We then calculate the inflation-adjusted dollar per performance, dividing the former by the latter. We average the dollar per performance if there are multiple releases within a year, and we linearly interpolate the dollar per performance if there are no releases for a specific year. Table D1 column 5 shows this data series.

Table D2: Cross Section of AI Pricing in 2023

Size Group	Log Sales	AI pricing Share	Adoption Rate	Observations
1	0.8516183	0.00%	0.00%	382
2	2.759726	0.00%	0.00%	383
3	3.460735	0.00%	0.00%	383
4	3.975862	0.00%	0.00%	382
5	4.383954	0.00%	0.00%	383
6	4.735429	0.00%	0.00%	383
7	5.013049	0.00%	0.00%	382
8	5.263219	0.83%	0.26%	383
9	5.52475	0.58%	0.52%	383
10	5.765324	1.95%	1.57%	383
11	6.020897	0.38%	1.05%	382
12	6.261518	1.29%	2.09%	383
13	6.494464	1.24%	1.31%	383
14	6.765912	0.63%	1.05%	382
15	7.022635	1.07%	2.09%	383
16	7.327437	0.88%	3.39%	383
17	7.672688	1.74%	4.71%	382
18	8.082669	1.59%	9.40%	383
19	8.609992	1.06%	11.49%	383
20	9.922308	3.69%	30.03%	383

Notes: The data source is our Lightcast Compustat Quarterly merged dataset in 2023. We exclude two firms that specifically may provide AI pricing as a service to other firms. In group 4, we exclude only one firm that adopts AI pricing, Citizen Inc., an insurance holding company providing a strategy of offering traditional insurance products in niche markets. In group 6, we exclude only one firm that adopts AI pricing, MicroStrategy Inc., a business service firm that provides business AI, mobile software, and cloud-based services.

Cross Section of the Size Adoption Correlations Our cross-section data for the size adoption correlations are taken from our Lightcast Compustat merged dataset for the year 2023. We sort the firm-quarter observations in sales and group them into twenty bins of an equal number of firm-quarter observations. Table D2 summarizes this data.