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 artificial intelligence (AI)-powered pricing and study its implications for firm performance, both on average and in response to monetary policy shocks. We use the online job postings data from Lightcast to measure the adoption of AI pricing. We infer that a firm is adopting AI pricing if it posts a job 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 more than tenfold since 2010. The rise of AI pricing jobs has been broad-based, spreading across more industries than other types of AI jobs. At the firm level, larger and more productive firms are more likely to adopt AI pricing. Firms that adopted AI pricing experienced faster growth in sales, employment, assets, and markups, and their stock returns are also more responsive 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 its demand function invests in AI pricing to acquire information.

Keywords: Artificial intelligence, AI-powered pricing, algorithmic pricing, price discrimination, monetary policy, technology adoption, firm performance

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 their macroeconomic impacts and related policy implications. One area that has received less attention but is equally important is the rise of AI-powered algorithmic pricing (henceforth, “AI pricing”). Unlike traditional price-setting methods, AI pricing algorithms can process vast amounts of information and adapt to real-time changes in demand and supply conditions. Recent studies have focused on the impact of AI pricing on market competitiveness or collusion in specific industries, such as online retailing (Aparicio, Eckles, and Kumar, 2023; Wang et al., 2023), housing rental (Calder-Wang and Kim, 2023), gasoline (Assad et al., 2024), and pharmaceutical industries (Brown and MacKay, 2023).

Many important questions related to the rise of AI pricing remain unanswered. For example, how rapidly has AI pricing grown over time? How widely has AI pricing been adopted? What types of firms adopt AI pricing? How does AI pricing affect firm performance, as measured by sales, employment, investment, and markups? And how does adopting this new pricing technology reshape 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 firm-level measure of AI pricing adoption 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 an AI pricing job. We aggregate all AI pricing job postings within each firm for a given period. To examine firm-level determinants of the adoption of AI pricing and its impact on firm performance, we merge our firm-level AI pricing data from Lightcast with the firms’ balance sheet information from Compustat and other aggregate variables.

We document five stylized facts about AI pricing.

1. AI pricing rose rapidly over time. The share of AI pricing jobs among all pricing jobs has surged more than tenfold from 2010 to 2024, with the sharpest increases occurring after 2015. 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. Although AI jobs account for a relatively small share of all jobs (peaking at 0.75% in 2022), AI pricing jobs represent a much larger share of all pricing jobs (peaking at 1.5% in 2021). Notably, 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 conventional pricing jobs more than one-to-one.

2. The increase in the share of AI pricing jobs after 2015 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 was concentrated in a few sectors, mainly information, manufacturing, finance and insurance, and professional and business services.

3. At the firm level, larger and more productive firms and those with higher R&D intensity are more likely to post AI pricing jobs.

4. 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. These correlations are stronger for larger firms.

5. The stock returns of firms that adopted AI pricing are more responsive to monetary policy shocks than non-adopters. A contractionary monetary policy surprise—constructed by Bauer and Swanson (2023) using high-frequency data based on FOMC announcements—reduces 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 faces incomplete information about its demand function. The firm produces a single good at a constant marginal cost and sells the good to a continuum of heterogeneous individuals with diverse observable characteristics. Demand is a high-dimensional function of these individual observables, and the firm can invest resources into pricing technology to learn about this 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 over conventional pricing. The AI pricing technology also entails a fixed cost, giving rise to a discrete choice of AI adoption, as observed in the data.

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 its intensity 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 it 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, since they can learn the demand function more effectively, enabling them to set their prices closer to the full-information optimal level. Finally, our model predicts that an increase in aggregate demand (e.g., due to monetary policy expansions) 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 makes contributions to the literature in three key areas. First, we contribute to the emerging economics literature on artificial intelligence and algorithmic pricing. The focus of this literature has been on how AI pricing changes firms' pricing decisions and market competitiveness in industrial organizations and businesses.[1] Recent studies have examined the implications of AI pricing for specific industries, including online retailing (Aparicio, Eckles, and Kumar, 2023; Wang et al., 2023), rental (Calder-Wang and Kim, 2023), gasoline (Assad et al., 2024), and pharmaceuticals (Brown and MacKay, 2023).[2] Complementing their work, our focus is on the adoption of AI pricing across the entire economy: We document the adoption of AI

[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. (2025) 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 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 pricing patterns and price stickiness by online sellers, but unfortunately, cannot precisely confirm AI pricing adopters.

pricing for the universe of US firms posting jobs online and show how such adoption affects firm performance and aggregate policies.

Second, our work is 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, 2024), 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, 2025), 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). Another closely related focus is on how firms use data in production and how it matters for the aggregate economy (Jones and Tonetti, 2020; Veldkamp and Chung, 2024; Baley and Veldkamp, 2025). Our findings show that AI pricing usage is also concentrated in large and high-productivity firms. Complementary to Babina et al. (2024), who study how general AI investment affects firm performance through increased innovation, we focus on AI as a new price-setting tool and study how AI pricing could affect firm performance, both on average and in response to monetary policy shocks.

Finally, our paper contributes to the macroeconomics literature on price stickiness. Before the rise of AI pricing, empirical studies found that prices were quite sticky. Bils and Klenow (2004) and Nakamura and Steinsson (2008) document significant price stickiness in offline markets for major goods and services, 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 sticky prices are costly, such that firms with more flexible prices have lower stock market return volatility in response to monetary shocks. The rise of AI pricing might fundamentally alter the frequency and magnitude of price adjustments and price discrimination, with implications for firm performance and monetary policy transmission. We show that AI pricing increases the sensitivity of firms' stock returns to monetary policy shocks, even after controlling for price adjustment frequencies.

Layout. The rest of the paper is organized as follows. Section 2 documents the economy-wide rise of AI 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 is correlated with long-term firm performance. Section 5 shows how AI pricing adoption affects monetary policy shock transmission to firm performance. Section 6 lays out the model and explores its predictions. Section 7 concludes.

2 The Rise of AI Pricing

In this section, we document the rise of AI pricing using data from Lightcast for online job postings. We identify leading firms that adopted AI pricing and examine the time-series trends and the cross-industry distributions of AI pricing jobs.

2.1 AI Pricing Versus Traditional Pricing

AI pricing differs from traditional pricing in three key ways. First, AI pricing relies on algorithm-based decision-making, where machine learning models automatically adjust prices based on data inputs, whereas traditional pricing often depends on manager-based decisions guided by human intuition and experience. For instance, DellaVigna and Gentzkow (2019) document the uniform pricing patterns in U.S. retail chains and argues that could be potentially attributed to managerial inertia. Second, AI pricing leverages more granular or even personalized data, enabling highly tailored pricing for individual customers or segments, while traditional pricing uses more aggregated data to set broader price points. Finally, AI pricing utilizes real-time data to dynamically adjust prices based on current market conditions, demand, and competitor actions, whereas traditional pricing primarily relies on historical data and slower, manual adjustments. These differences make AI pricing more adaptive, precise, and responsive compared to traditional methods.

2.2 Lightcast Data

We use the Lightcast data, formerly Burning Glass, on U.S. job postings from 2010Q1 to 2024Q1.[3] 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 job postings in the U.S. from 2010 onward, representing approximately 60–70% of all job postings, both online and offline. The company employs a sophisticated, multi-step deduplication algorithm to prevent double-counting job posts posted on multiple job boards or across multiple periods, ensuring each posting corresponds to a distinct job posting.[4] The representativeness of Lightcast data is stable over time at the occupation level. Acemoglu et al. (2022b) confirmed that the total job posts 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 pricing job posts by identifying postings that require AI-related skills and mentioning the keyword "pricing." This helps us identify businesses that are likely to engage in AI pricing, as AI-skilled pricing teams are crucial for its implementation. Our analysis focuses on the firm level, as pricing algorithms are typically developed and applied at the firm level rather than at the establishment level.[5] Specifically, we first identify all AI-related and pricing job postings. We then identify AI pricing jobs as those at the intersection of these two groups. For each firm, we measure the intensity of AI pricing jobs by the share of AI pricing job postings in all pricing job

[3]Lightcast provides job posting data at a monthly frequency. We aggregate the data to the quarterly frequency because we need to merge it with the quarterly firm-level balance sheet information in Compustat.

[4]Lightcast applies a unique two-step approach to deduplication. In the first step, they use intelligence contained within the scraping spiders to identify a new advertisement for that source on a source-level basis. In the second step, they use normalized fields, including job title, company, and location, and check to see if these fields have been used in new advertisements found in another source. They check across 60 days of data to identify duplicates. For more details, please refer to https://kb.lightcast.io/en/articles/6957661-how-does-lightcast-handle-duplicate-postings. Such a sophisticated deduplication algorithm could largely mitigate the duplications. However, if AI-related job posts have more (fewer) duplications beyond 60 days, then the job posting data would be over-counting (under-counting) AI-related job posts.

[5]For instance, Calder-Wang and Kim (2023) shows that RealPage uses a centralized price-setting algorithm for all rental apartments across all cities in the U.S., Assad et al. (2024) shows the same centralized algorithmic price-setting across gasoline stations in Germany, and Spann et al. (2025) provides summaries across various industries.

postings. Although it does not perfectly measure such demand, this measure could reflect a firm's labor demand for AI pricing needs.[6]

2.3 Measuring AI Pricing Adoption

To construct our measures on the intensity of AI pricing, we 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.[7] 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 distinct 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.

AI Pricing Measures 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, with a 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 $N_{j,t}^{AI}$,

[6]Our measure has limitations in not capturing AI pricing demand perfectly. For example, a firm can redeploy some existing AI workers to handle pricing tasks without posting a new job opening. For another example, a firm can delegate AI pricing tasks to a large company, in which case, they are performing AI pricing but not hiring AI pricing workers. We cannot address the former case, but since most firms are public, they would likely hire if they have AI pricing demand, even though they could also reallocate other AI workers to perform AI pricing tasks. For the latter case, we check robustness, excluding IT or professional & business services firms.

[7]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	13.329	189.182	1	147846
Pricing Jobs	2662686	0.105	5.466	0	6905
AI Jobs	1614194	0.064	2.837	0	2835
AI Pricing Jobs	24461	0.001	0.124	0	149
Observations	25414949	*Firm-Level at Monthly Frequency*			

Notes: This table summarizes our Lightcast Job Posting Data from 2010Q1 to 2024Q1 at a monthly frequency. 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.

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 each scope $s = \{1, 2, 3, all\}$. We then compute firm-level non-cumulative intensity measures ($Share_{j,t}^{x/y} = N_{j,t}^{x}/N_{j,t}^{y}$) and cumulative intensity measures ($Cum.Share_{j,t}^{x/y} = \sum_{t=0}^{t} N_{j,t}^{x} / \sum_{t=0}^{t} N_{j,t}^{y}$) for firm j of x over y at different time frequencies $t = \{\text{yearly, quarterly}\}$ to meet our various data analysis needs. Since a successful hire typically affects a firm's capabilities over multiple years, our primary focus is on the cumulative intensities of AI-related pricing jobs within pricing jobs ($Cum.Share_{j,t}^{AP_s/P_s}$) across all scopes. In contrast, we use the non-cumulative intensity to illustrate the aggregate time trends of AI pricing adoption over time, as it can indicate the immediate periodic relative labor demand in AI pricing and is comparable to the literature, such as Acemoglu and Restrepo (2018) and Babina et al. (2024).

Advantages and Limitations A main advantage of using the Lightcast job postings data to infer the aggregate trends and cross-sectional distributions of AI pricing adoption is that it allows us to construct a panel of firm-level data covering the entire economy, with detailed information on the timing and intensity of AI pricing adoption.[8]

However, there are several important limitations in using the job postings data for measuring AI pricing adoption. First, our measure is an input-based measure, which is different from the outcome-based measures commonly used in industrial organization studies (Assad et al., 2024).

[8] Following the same procedure, a researcher could use the Lightcast job postings data to construct measures for other AI-related corporate activity, such as AI marketing, AI risk management, and AI hiring.

Posting a job is not the same as hiring an AI pricing worker, although changes in job postings provide a clear signal of changes in firms' demand for AI pricing labor, and thus give us an indirect measure of AI pricing adoption. In addition, an outcome-based measure has significantly higher data requirements than our input-based measure, such that it is typically applied only to specific firms and specific products. Second, some firms may use third-party vendors for AI pricing. This is especially relevant for small firms that lack the resources to build in-house algorithmic pricing. Our job postings data does not allow us to detect such indirect adoption of AI pricing. This may lead to an under-estimation of AI pricing adoption, especially among small firms.

Third, some jobs were posted repeatedly (i.e., duplicated postings), which may not indicate multiple hires but rather hiring difficulties. This could lead to over-estimation of AI pricing adoption. Although Lightcast has a de-duplication algorithm that mitigates the repeated posting issue, the algorithm is imperfect (e.g., it removes job postings from the past 60 days, but not from the entire history). Overall, however, repeated postings could also lead to over-estimation of the demand for traditional pricing labor and general AI-related labor as well. Thus, it is not clear how it would affect the overall trends and cross-firm variations of the relative demand for AI pricing labor.

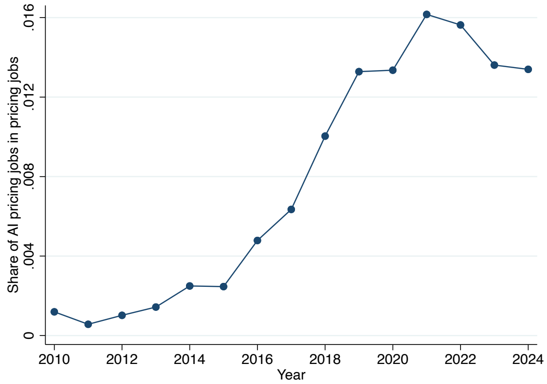
Despite these limitations, our input-based measure remains a valuable and scalable tool for capturing firm-level AI pricing adoption across broad sectors and over time. It enables systematic comparisons of AI pricing adoption patterns, even when detailed output data are unavailable.

2.4 Aggregate Trends

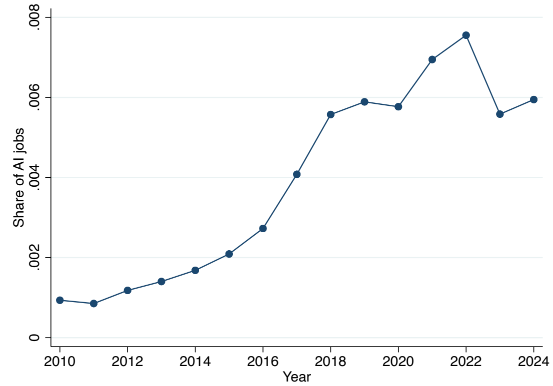
Our evidence indicates that the share of non-cumulative AI pricing job postings has risen sharply, increasing more than ten times from 2010 to 2024. Panel (a) of Figure 1 shows the fraction of non-cumulative all-scope pricing job postings that we classify as AI-related: this fraction starts at 0.12% in 2010. It increases sharply after 2015, reaching a peak of 1.61% in 2021, before slowing modestly to 1.34% in 2024:Q1. The trend is consistent across different scopes of pricing job measures, as shown in Appendix A.3.

The rise of AI pricing parallels the increase in all AI-related jobs. During the same period, the share of AI-related jobs in all job postings has increased from about 0.1% in 2010, growing sharply

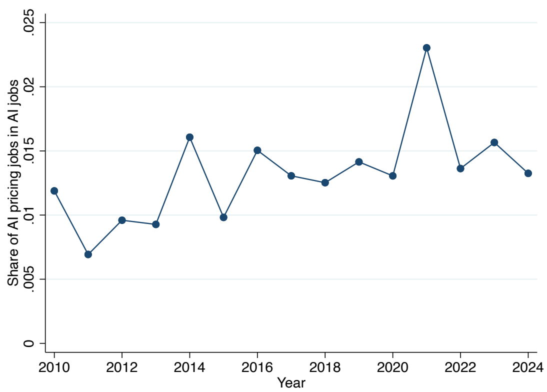
Figure 1: Aggregate Time Trends of AI Pricing, Pricing, and AI Jobs



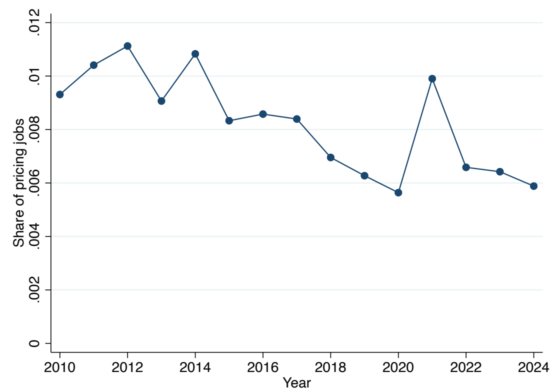
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Jobs in All Jobs



(c) Share of AI Pricing in AI Jobs



(d) Share of Pricing Jobs in All Jobs

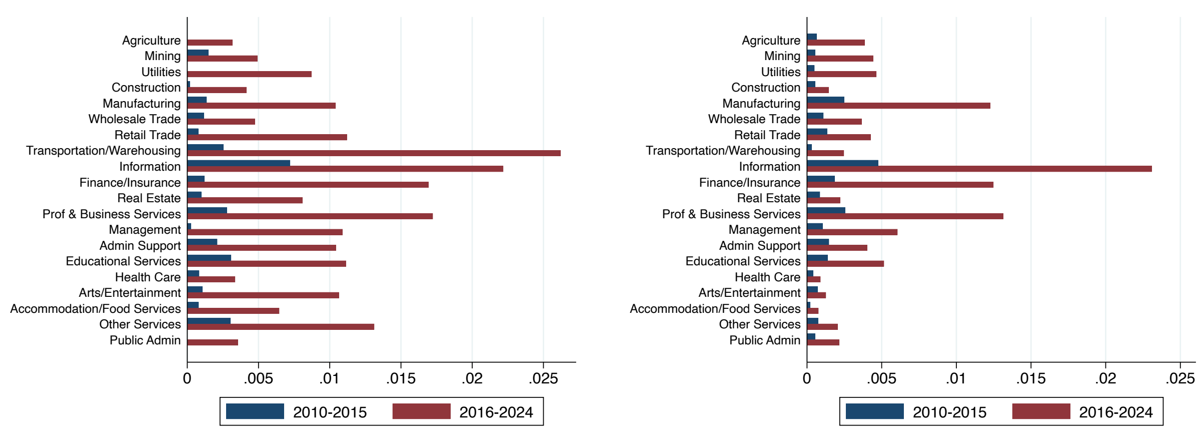
Notes: This figure plots the aggregate time trends of non-cumulative intensities of AI pricing, pricing, and AI jobs at the annual frequency. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022b)'s narrow category classification. Pricing jobs are measured in three scopes. The first scope only includes the most narrowly defined pricing jobs, which must include exactly the keyword "pricing" in their job titles. 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 these measures, we could construct a panel of job postings for firm j at time t. The measures include the number of jobs $N_{j,t}$, the number of AI jobs $N^{AI}_{j,t}$, the number of pricing jobs $N^{P_s}_{j,t}$ with scope $s = \{1, 2, 3, all\}$, and the number of AI pricing jobs $N^{AP_s}_{j,t}$ with scope $s = \{1, 2, 3, all\}$. We aggregate all measures to the firm level non-cumulative intensity $Share^{x/y}_{j,t} = N^x_{j,t}/N^y_{j,t}$. The three scopes ' robustness checks of alternative measures separately are presented in Figure A4.

after 2015 to a peak of about 0.75% in 2022 (Panel (b)), which is similar to the trend in the share of AI-related jobs documented by Acemoglu et al. (2022b) and Babina et al. (2024). As a result, the share of AI pricing jobs in all AI-related jobs has stayed relatively stable (Panel (c)). In contrast to the tenfold increase in the share of AI pricing jobs in all pricing jobs, the share of pricing jobs in all job postings has declined by about 40%, from 0.93% in 2010 to 0.59% in 2024Q1 (Panel (d)), implying a large displacing effect of non-AI pricing workers by the rise of AI pricing. Again, these patterns are robust to different scopes of pricing job measures, as we show in Appendix A.3.

2.5 Variations Across Industries

We now examine how the sharp increases in AI pricing job postings after 2015 vary across industries, and how such cross-sectional variations compare with those of all AI-related job postings.

Figure 2: Variations Across Two Digit Industry Sector



(a) Share of AI Pricing in Pricing Jobs

(b) Share of AI Jobs in All Jobs

Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs for 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 their job titles. 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. We extract AI pricing jobs at the intersection of both AI-related and pricing jobs in all three scopes.

Figure 2 shows that the share of AI pricing jobs in all pricing jobs has increased after 2015 in most 2-digit NAICS industries, with substantial cross-sectional variations in its expansion. The information industry had the highest initial share of AI pricing jobs (about 0.7%) before 2015, and the share increased sharply to 2.2% after 2015. The transportation industry has experienced an even sharper increase in AI pricing after 2015, with a share exceeding 2.5%. Both the finance and insurance industry and the professional and business services industry saw a substantial rise in AI pricing from relatively low levels in 2010-2015 to about 1.7% in 2016-2024. Other industries, such as agriculture, mining, construction, wholesale trade, and healthcare, had lower shares of AI pricing jobs in both sub-periods, indicating limited applicability or slower adoption of AI in pricing within these sectors. Even in those sectors, the share of AI pricing has increased substantially after 2015.

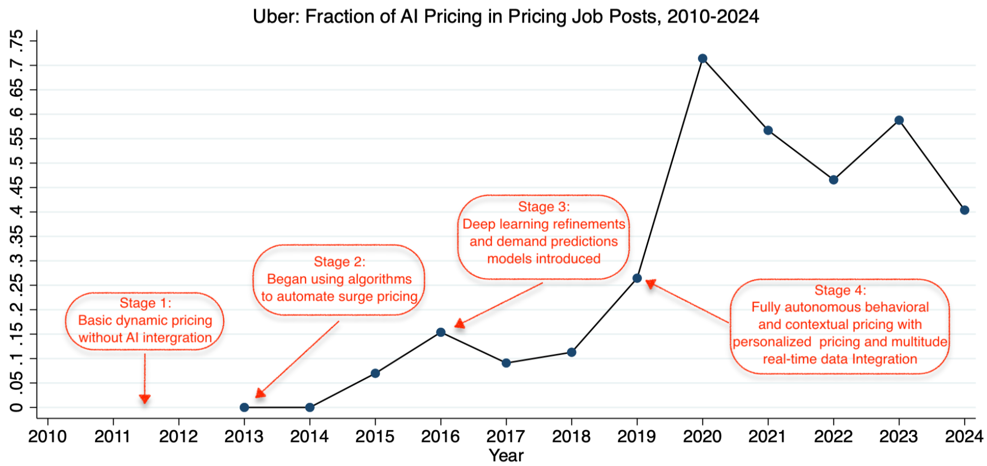
In contrast to the widespread increases in the share of AI pricing jobs, Panel (b) shows that the post-2015 increases in the share of AI jobs in all jobs have been concentrated in four industries: information, manufacturing, professional and business services, and finance and insurance. In the post-2015 period, the information sector had the largest share of AI-related posts, at around 2.3%. The other 3 sectors had a share of about 1.3% during the same period. The share of AI-related job postings in the remaining industries stayed at low levels. In contrast, the share of AI pricing jobs has grown rapidly in a broader set of industries, including transportation, information, business services, finance, and retail trade.

2.6 The Case of Uber

We use the case of Uber as a validation of our measure of AI pricing jobs. We show that our measure could roughly reflect the firm's adoption of AI pricing. We look at Uber for two reasons: (1) Uber is an early adopter of AI pricing, and (2) Uber is the most transparent company about its stages in AI pricing adoption, potentially because they need to educate customers to accept AI pricing. Therefore, we combine our measure of AI pricing for Uber, Uber Newsroom (www.uber.com/newsroom) and Uber Blog (www.uber.com/blog), where Uber posts their announcements and summaries of algorithm adoptions and future plans, which provide a useful case study for validating our measure of AI pricing. We divide Uber's AI pricing adoptions roughly into four different stages, as shown below in Figure 3.

In the first stages, Uber implemented basic rule-based dynamic pricing to balance supply and demand early on. In their newsroom article *"A Walk Through Surge Pricing, 2010-2012"*, they explained that during periods of high demand like holidays or inclement weathers, prices would

Figure 3: Timeline of AI Share of Pricing Job Posts by Uber



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. In our data, we also do not find any AI pricing job posts by Uber. In the second stage, around 2012, Uber began using algorithms to automate surge pricing, which monitors real-time data from rides, locations, and drivers to adjust prices. They clarified in their December 2012 newsroom article *"NYE 2012 Surge"* on how they conduct dynamic surge pricing. Our measure does not capture it in 2012 because these tasks are conducted by non-pricing AI engineers. In our measure, we start to observe initial appearance and fast growth of Uber's AI pricing job posts since the beginning of year 2013.

In the years that followed, Uber's AI pricing became increasingly sophisticated. As summarized in a blog article in November 2018 (*"Scaling Machine Learning at Uber with Michelangelo,"*), Uber has increased usage of advanced machine learning, including new pricing and demand prediction models in the three years since 2015. This represents the third stage of AI pricing adoption by Uber. In the final stage in 2019, Uber posted the article *"How Uber Leverages Applied Behavioral Science at Scale"* to discuss how the company leveraged psychology and behavioral economics, but they never discussed pricing ever since. Meanwhile, they received much attentions and criticisms on their behavioral pricing from major newspapers such as Forbes, The Guardian, and Fortune. Uber CEO Dara Khosrowshahi admitted that they are conducting behavioral pricing in an earning conference call in 2024 (Computer weekly). In our measure, we find that Uber's AI share of pricing job posts has surged after 2018 and has remained high ever since.

In summary, although our measure of AI pricing does not perfectly reflect Uber's AI pricing usage, it aligns roughly with the timeline of Uber's public announcements of AI pricing adoption. In Appendix A.2, we provide further narrative evidence using the cases of Amazon and JP Morgan Chase to validate our measure of AI pricing jobs.

2.7 Robustness Checks

We provide robustness checks in Online Appendix A. We include news articles and industrial reports (A.1), more detailed case studies of Uber and two other leading firms (A.2), and alternative measures of aggregate trends (A.3), showing clear transition paths in the advancements of AI pricing. We also perform checks for leading firms (A.4), (A.5), and examine industry variations with different scopes (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 different 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, and R&D-intensive 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.

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

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	131647	0.09	0.21	0	1
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%. Additionally, we constrain our R&D intensity to be between 0 and 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 count the cumulative number of AI pricing job postings $APN_{j,t}$, 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 cumulative number of AI pricing job postings $APN_{j,t}$ by the cumulative number of pricing job postings. We use cumulative rather than periodic measures to reduce the noise caused by large short-run fluctuations in job postings.

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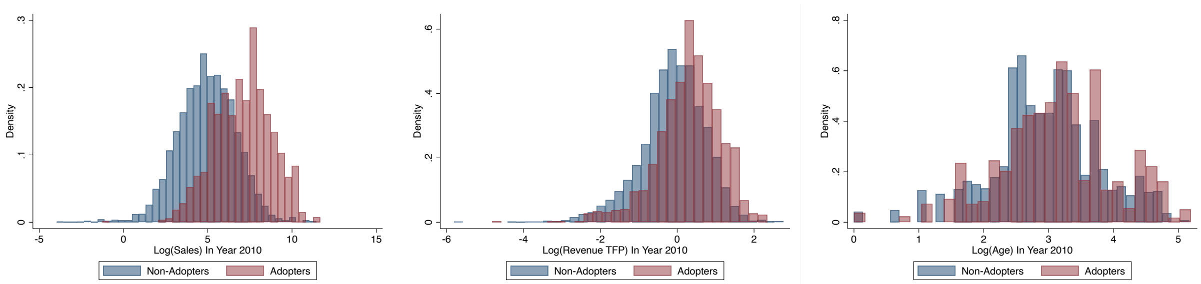
3.2 Distributions of Adopters and Non-Adopters

We begin by examining the ex-ante 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 4 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 4: 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 of AI adoption in Figure B4.

Figure 4 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 ($saleq - cogsq$). We then regress the logged value-added on fixed capital ($ppentq$) and number of employees (emp), using the Solow residuals as the logged revenue TFP.[9] Panel (b) reveals a similar pattern: adopters have higher TFP values, suggesting that more productive firms are more likely to post AI pricing job posts. 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.

[9]We follow Foster, Haltiwanger, and Syverson (2008) to calculate our OLS Solow residuals. Since a quarterly number of employees is not available, we use the annual number of employees instead. Meanwhile, we use the Bureau of Labor Statistics NAICS 4-digit PPI deflator to deflate fixed capital and value-added.

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 following 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 job post 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, return on assets (ROA), cash-to-assets ratio, and debt-to-assets ratio, all winsorized at the top and bottom 1% at the year quarter frequency.[10] We also include industry fixed effects (γ_s) and quarter fixed effects (δ_q) to control for unobserved heterogeneity. These regressions include only firm-quarter observations that were available in 2010, so the total number of observations was reduced to between 6342 and 7797, depending on the controls. Since our adoption dummy is a binary variable, we estimate a probit regression and find similar results for size, productivity, and R&D intensity, as reported in the Online Appendix B.3.

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.

[10] 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). Markup is calculated as the ratio of sales to the costs of goods sold.

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***									0.107***
	(0.002)									(0.003)
Log TFP 2010		0.103***								0.020***
		(0.006)								(0.007)
Log Age 2010			0.032***							-0.004
			(0.005)							(0.005)
Tobin's Q 2010				0.011***						0.011***
				(0.003)						(0.004)
Log Markup					0.016**					0.021*
					(0.007)					(0.012)
R&D/Sales 2010						-0.000				0.335***
						(0.000)				(0.057)
ROA 2010							-0.225***			0.122
							(0.081)			(0.098)
Cash/Assets 2010								-0.104***		0.004
								(0.023)		(0.033)
Debt/Assets 2010									0.071***	-0.053**
									(0.020)	(0.022)
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	7797	7776	7787	7299	6342
adj. R^2	0.205	0.060	0.022	0.018	0.017	0.017	0.017	0.019	0.015	0.236

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 post between 2010Q1 and 2024Q1. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$.

In Column (10), we pool all explanatory variables to run a "horse-race" regression. The significant variables are sales, TFP, and the R&D to sales ratio. Log sales have a coefficient of 0.107, indicating that a 10% increase in sales is associated with a 1.07% higher probability of adopting AI pricing, controlling for other firm characteristics. Log TFP has a coefficient of 0.020, suggesting that a 10% increase in TFP is related to a 0.20% 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 0.335, indicating that a 10% increase in R&D investment corresponds to a 3.35% higher probability of AI pricing adoption. Additionally, log markup is marginally significant and positive, while the debt-to-assets ratio is significantly negative, indicating that more leveraged firms are less likely to adopt AI pricing. Other variables such as age,

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***									4.161***
	(0.210)									(0.233)
Log TFP 2010		5.485***								1.585***
		(0.547)								(0.585)
Log Age 2010			1.417***							0.446
			(0.502)							(0.413)
Tobin's Q 2010				1.126***						0.112
				(0.291)						(0.289)
Log Markup 2010					0.594					0.600
					(0.627)					(0.897)
R&D/Sales 2010						-0.006				10.122**
						(0.024)				(4.426)
ROA 2010							-8.341			6.158
							(7.489)			(7.642)
Cash/Assets 2010								1.962		5.283**
								(2.134)		(2.556)
Debt/Assets 2010									1.721	-2.635
									(1.388)	(1.677)
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	7797	7776	7787	7299	6342
adj. R^2	0.053	0.028	0.016	0.016	0.014	0.014	0.014	0.014	0.007	0.078

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 posts posted between 2010Q1 and 2024Q1. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$.

Tobin's Q, ROA, and cash-to-asset 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 pricing job postings. The specifications are as follows:

$$\{APN_{j,2024Q1}, APS_{j,2024Q1}\} = \beta x_{j,2010q} + \gamma_s + \delta_q + \epsilon_{jq}, \tag{2}$$

where all the other specifications are the same as regression specification (1). The $APS_{j,2024Q1}$ regressions further require that the observations must have non-zero pricing job postings so that an $APS_{j,2024Q1}$ indicator is non-missing, so the total number of observations was reduced to between 5826 and 6244, depending on the controls.

Table 5: Firm-level Determinants of AI Pricing 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***									0.001
	(0.000)									(0.000)
Log TFP 2010		0.004***								0.003**
		(0.001)								(0.001)
Log Age			-0.002***							-0.003***
			(0.001)							(0.001)
Tobin's Q 2010				0.001***						0.001
				(0.000)						(0.001)
Log Markup 2010					0.001					-0.002
					(0.001)					(0.002)
R&D/Sales 2010						-0.000				0.021**
						(0.000)				(0.009)
ROA 2010							0.008			-0.017
							(0.017)			(0.025)
Cash/Assets 2010								0.008**		-0.000
								(0.004)		(0.005)
Debt/Assets 2010									0.003	0.005
									(0.003)	(0.003)
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	6244	6232	6240	5875	5286
adj. R^2	0.010	0.012	0.012	0.011	0.009	0.009	0.009	0.010	0.010	0.015

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 posts posted between 2010Q1 and 2024Q1 divided by the total pricing posts posted during the same period. The independent variable, $x_{j,2010q}$, represents firm j's characteristic in quarter q of 2010, for $q = Q1, Q2, Q3, Q4$.

In Table 4, we replace the dependent variable in regression specification (1) with firms' cumulative 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 job posts.

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 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 R&D

to sales ratio has a significantly positive coefficient, with a coefficient of 0.021.

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.4. We find the adoption patterns of AI pricing are consistently significant in size, productivity, and R&D intensity, 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 that post a larger share of AI pricing job openings positively correlate with 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.

We examine whether firms that hire a larger share of AI pricing workers in their pricing teams see faster growth over time. To explore this, we specify a long-difference 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:

$$\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \delta_q + \epsilon_j \tag{3}$$

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. $Z_{j,t1}$ includes a set of controls, including the share of AI jobs, the share of pricing jobs, and firm balance sheet characteristics in $t1$ that determine AI pricing adoption from Section 3 (size, TFP, and R&D intensity). Finally, γ_s is the two-digit NAICS industry fixed effect, and δ_q represents the quarter fixed effects.

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***	1.137***	0.996***	0.875***	1.134***	1.197***	0.259	0.259**
	(0.332)	(0.305)	(0.286)	(0.268)	(0.343)	(0.332)	(0.166)	(0.121)
Share of AI		-0.371		-0.637		-0.702		-0.628**
		(0.698)		(0.609)		(0.760)		(0.276)
Share of Pricing		0.068		0.231		0.080		-0.050
		(0.190)		(0.236)		(0.207)		(0.075)
Log Sales		-0.103***		-0.121***		-0.133***		0.009***
		(0.009)		(0.008)		(0.010)		(0.003)
Log TFP		0.046**		0.175***		0.106***		-0.092***
		(0.019)		(0.018)		(0.021)		(0.008)
R&D/Sales		1.559***		1.202***		1.002***		0.318***
		(0.179)		(0.165)		(0.195)		(0.071)
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	3777	3677	3471	4025	3781	4014	3777
adj. R^2	0.064	0.145	0.086	0.188	0.049	0.121	0.018	0.059

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: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \delta_q + \epsilon_j$, 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. $Z_{j,t1}$ 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, and δ_q represents the quarter fixed effect.

Main Results Table 6 shows the estimates for the above regression. In columns 1, 3, 5, and 7, we include only industry- and quarter-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 (size, TFP, and R&D-intensity); 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 cross-sectional sample of 4,014 firm-quarter observations in the year 2010. 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 1.137% cumulative growth in sales. In columns 3 and 4, we find a positive association with employment growth similar to the relationship with sales but with a smaller magnitude. Columns 5 and 6 show that increases in AI pricing intensity are also associated with increases in firm assets. Finally, columns 7 and 8 show that firms that increased their usage of AI pricing also experienced increases in 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 0.259% cumulative growth in markup. Including firm-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 adopting AI pricing is positively associated with firm growth. However, it is important to note that the correct interpretation of our results is not that adopting AI pricing, without any other adjustments to the firm operations, 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.[11]

Building an AI pricing team could be very costly initially, but once adopted, firms with more products and operating across more sub-markets could benefit more. Table 7 shows that the benefits from AI pricing adoption are not evenly distributed across firms of different sizes, as measured by their 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-

[11] Our findings are consistent with Corhay et al. (2025) such that firms with higher proportions of data scientists have higher markups, higher information quality proxied by lower sales forecast errors, and higher stock returns.

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

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}\times$ Size Small	0.606	0.402	0.189	0.182	-0.150	-0.102	0.116	-0.152
	(0.516)	(0.504)	(0.433)	(0.437)	(0.531)	(0.546)	(0.263)	(0.198)
$\Delta APS_{j,[2010,2023]}\times$ Size Medium	2.008***	1.749***	1.258**	0.751	2.324***	2.085***	1.024***	1.189***
	(0.605)	(0.561)	(0.524)	(0.502)	(0.622)	(0.607)	(0.309)	(0.220)
$\Delta APS_{j,[2010,2023]}\times$ Size Large	2.919***	3.182***	3.162***	2.983***	2.429***	2.855***	-0.456	-0.197
	(0.875)	(0.822)	(0.739)	(0.717)	(0.900)	(0.890)	(0.446)	(0.323)
Controls	N	Y	N	Y	N	Y	N	Y
Industry×Szie Group FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4005	3777	3677	3471	4016	3781	4005	3777
adj. R^2	0.135	0.182	0.187	0.234	0.135	0.171	0.061	0.112

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: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} \times j_{size} + \Gamma Z_{j,t1} + \gamma_s \times j_{size} + \delta_q + \epsilon_j$, 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. j_{size} is the size dummy in 2010. $Z_{j,t1}$ 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, $\gamma_s \times j_{size}$ in the two-digit NAICS industry × size dummy fixed effect, and δ_q represents the quarter fixed effect.

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, given the fixed costs of acquiring big data and setting up AI pricing teams, larger firms are more likely to benefit from AI pricing, as it enables them to adjust prices based on faster and more accurate estimates of changes in market conditions.[12]

Robustness Checks We examine the robustness of the long-differences results in Online Appendix C. We find the firm performance patterns of AI pricing remain consistent with our main results across various robustness checks, including: excluding finance and utility firms (C.1), excluding IT firms (C.2), excluding business and professional services firms (C.3), excluding all the above firms (C.4), excluding largest firms in top 1%, 5%, or 10% (C.5), or controlling for changes in AI share and pricing share (C.6).

[12]We find that the firms that benefit the most in markup growth are the middle-sized firms. This could come from that firm size is not monotonically related to markups (Dedola et al., 2025). Meanwhile, the relation between markup and firm size depends on how we measure markup from the production side: the relation would be different if you measure markup using sales/intermediate goods vs. sales/wage bills (Raval, 2023).

5 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 and 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, conditional on AI pricing adoption, reflect how the firms' market value depends on their adoption of AI pricing.

5.1 Merge to CRSP, Monetary Shocks, FPA, and Upstreamness

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. We use Bauer and Swanson (2023)'s series for the period from January 27, 2010, to December 11, 2019, capturing a total of 81 FOMC announcement events.[13] We then extract the daily stock return of all firms in our Compustat sample 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 25 bps. We denote the adjusted monetary shock at event date e as MP_e. So, a one-unit increase in the variable MP_e reduces the one-year rate by 25 basis points. 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. Finally, we also include the

[13] The monetary policy shock that we use is the measure of the monetary policy surprises constructed by Bauer and Swanson (2023), which is computed as the first principal component of changes in the interest rates of the first four quarterly Eurodollar futures contracts, ED1 to ED4, around FOMC announcements. Adams and Barrett (2025) estimate that this shock is largely driven by immediate federal funds rate surprises and short-term forward guidance. The measure is scaled such that a one-unit change in the first principle component corresponds to a one-percentage point change in the ED4 rate, which is a one-year interest rate. We follow the approach of Bauer and Swanson (2023) to orthogonalize the raw measure to information available before FOMC announcements. In particular, the orthogonalized monetary policy surprise measure is the residuals from regressing the raw monetary policy surprises on the six macro and financial variables listed in Table 1 of Bauer and Swanson (2023). We do not use the post-COVID sample because the Bauer-Swanson orthogonalized shock series is not available for 2020. Our results are robust to using the raw (unadjusted) monetary policy surprise measure.

Table 8: Summary of Variables in Lightcast-Compustat-CRSP-Merged Data

Variables	Obs.	Mean	Std.Dev.	Min	Max
MP_e	81	-0.0226	0.1189	-0.2672	0.3240
FPA_s	134	0.1420	0.1310	0.0334	0.7613
UP_s	142	1.9791	0.7963	1.0000	3.7484
Stock Returns (%)	180236	0.0919	3.0169	-65	224
$APS_{j,t-1}$	104963	0.0044	0.0484	0	1
$\mathbb{1}^{AP}_{j,t-1}$	180362	0.4500	0.4975	0	1
Share of AI	172332	0.0042	0.0289	0	1
Share of Pricing	172332	0.0126	0.0540	0	3
Log Sales	169976	5.3198	2.0305	-7	12
Log Age	163336	3.0145	0.8635	0	5
Log TFP	152351	0.0952	0.8796	-8	6
Log Tobin's Q	172011	0.5488	0.5630	-1	4
R&D/Sales	180362	0.1198	0.2723	0	1
Cash/Asset	172154	0.1832	0.2196	0	1
Log Markup	169460	0.6477	0.8812	-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 noise caused by large short-run fluctuations in job postings.

industry-level upstreamness from Antràs et al. (2012) to test whether downstream firms that are closer to more complex consumer markets would benefit more from AI pricing adoption. Table 8 summarizes the newly merged variables of monetary shocks, frequency of price adjustments, daily stock returns, and other firm-level variables.

5.2 Baseline Empirical Specification and Results

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

$$\begin{aligned} R_{j,e} =& \beta_0 + \beta_1 MP_e + \beta_2 MP_e \times APS_{j,t-1} + \beta_3 APS_{j,t-1} \\ &+ \beta_4 Z_{j,t-1} + \beta_5 FPA_s + \beta_6 MP_e \times FPA_s + \gamma_j + \epsilon_{je}, \end{aligned} \tag{4}$$

where $R_{j,e}$ denotes the daily stock return of firm j in the event date e and MP_e is our measure of monetary policy shocks. The term $APS_{j,t-1}$ denotes the share of the firm's cumulative AI pricing jobs in all pricing jobs, lagged by one quarter.[14] The regression includes a set of one-quarter lags of firm-level control variables denoted by $Z_{j,t-1}$, including the share of AI jobs in all jobs, the share of pricing jobs in all jobs, log sales, log age, log TFP, log Tobin's Q, cash ratio, and firm-level markup. The regression also controls for the frequency of price adjustment (FPA_s) at the 6-digit industry level of NAICS and its interaction with the monetary policy shock. The regression also includes firm fixed effects (γ_j). For robustness, we consider an alternative specification that includes event fixed effects, in which case, the direct effects of monetary policy shocks are absorbed by the event fixed effects. For further robustness, we estimate a regression that includes the interactions of monetary policy with all the firm-level controls ($MP_e \times Z_{j,t-1}$) in regression 4 (see the Online Appendix D.2.1).

Table 9 presents the result of our baseline regression specification (4), From all columns except 4 and 8, which control for event fixed effects, we find that a 25 bps unexpected monetary expansion causes stock returns to rise by about 2.5 to 3.0 percentage points. Firms with a higher share of AI pricing benefit significantly 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 15% share of AI pricing (e.g., Amazon), the stock return responses would be topped up by nearly one additional percentage point ($6.464 \times 0.15 \approx 0.97$). This magnitude is statistically significant and economically meaningful. This magnitude of stock return responses is comparable to the effects of increasing the frequency of price adjustment by about 2.5 standard deviations.[15]

[14] In Online Appendix D.1, we estimate a similar specification, where we use the one-quarter lag of the cumulative incidence of AI pricing adoptions (i.e., the dummy indicator $\mathbb{1}^{AP}_{j,t-1}$). We find that the qualitative results are similar.

[15] The point estimate of the coefficient on the interaction term $MP_e \times FPA_s$ shows that, for a firm in an industry

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP_e	2.426***	2.490***	2.414***		2.887***	2.959***	2.930***	
	(0.068)	(0.072)	(0.074)		(0.149)	(0.154)	(0.157)	
$MP_e \times APS_{j,t-1}$	3.195**	2.985**	2.873**	3.399***	6.967**	6.501**	6.073**	6.464**
	(1.358)	(1.398)	(1.422)	(1.285)	(2.895)	(2.772)	(2.876)	(2.596)
$APS_{j,t-1}$	0.153	0.006	0.047	0.201	0.329	0.407	0.378	0.372
	(0.166)	(0.175)	(0.449)	(0.406)	(0.337)	(0.337)	(0.675)	(0.609)
$MP_e \times FPA_s$					0.387***	0.357***	0.342***	0.384***
					(0.129)	(0.130)	(0.131)	(0.118)
FPA_s					0.026*	0.014		
					(0.015)	(0.017)		
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	109802	96656	96656	96656	28043	24556	24556	24556

*Robust standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01.*

Notes: This table shows the estimation results under the empirical specification in Eq. (4), where $APS_{j,t-1}$ is the firm-level share of AI pricing jobs in all pricing jobs, lagged by one quarter. The key independent variable is the interaction between the AI pricing share and the monetary policy shocks. The regression includes controls for the frequency of price adjustment (FPA_s) at the NAICS 6-digit industry level and its interactions with the monetary policy shocks. In addition, the regression includes the same set of firm-level controls as in the long-difference regressions, including (1) the lagged firm-level markup, the lagged firm-level share of AI workers, and the lagged share of pricing workers, and (2) the lagged firm-level characteristics, including log sales, log age, log TFP, log Tobin's Q, and cash ratio. The regression also includes firm and event fixed effects in some specifications.

5.3 Downstream versus Upstream Firms

Monetary policy shocks may have heterogeneous effects on firms' stock returns conditional on their AI pricing adoptions. We now examine whether downstream and upstream firms respond differently to the shock. As firms move from upstream to downstream, approaching more complex consumer markets, they may encounter more complex pricing tasks, making AI pricing adoption more important to them. This is also evident in our data, where more upstream industries exhibit a higher frequency of price adjustments, as reflected in a positive correlation $Corr(UP_s, FPA_s) = 0.2$ in our sample.

To examine whether AI pricing adoption leads to differential responses of stock returns for

with the frequency of price adjustments that is one standard deviation above the mean, an expansionary monetary policy shock (equivalent to a 25 basis point decline in the one-year nominal interest rate) raises its stock return by an additional 0.384 percentage point. In comparison, moving from a firm without AI pricing to Amazon with $APS = 0.15$, the additional increase in stock returns is comparable to raising FPA_s by $6.464 \times 0.15/0.384 = 2.525$ standard deviations.

upstream versus downstream firms, we estimate the empirical specification

$$
\begin{aligned}
R_{j,e} = \beta_0 &+ \mathbb{1}_j^{Up} \times \left(\beta_1^{up} MP_e + \beta_2^{up} MP_e \times APS_{j,t-1}\right) \\
&+ (1 - \mathbb{1}_j^{Up}) \times \left(\beta_1^{down} MP_e + \beta_2^{down} MP_e \times APS_{j,t-1}\right) \\
&+ \beta_3 APS_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 FPA_s + \beta_6 MP_e \times FPA_s + \gamma_j + \epsilon_{je},
\end{aligned}
\tag{5}
$$

where $\mathbb{1}_j^{Up}$ is a dummy indicator of upstream firms, which equals one if the upstreamness of firm j is above the mean level and zero otherwise. The other variables are the same as in Eq. (4).

Table 10: Stock Return Response to Monetary Shocks: Downstream vs Upstream

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$MP_e \times \{\mathbb{1}_j^{Up} = 0\}$	2.904***	3.016***	2.994***		2.941***	3.051***	3.019***	
	(0.198)	(0.201)	(0.203)		(0.202)	(0.204)	(0.207)	
$MP_e \times \{\mathbb{1}_j^{Up} = 1\}$	2.804***	2.826***	2.785***		2.892***	2.897***	2.864***	
	(0.207)	(0.217)	(0.220)		(0.252)	(0.262)	(0.265)	
$MP_e \times \{\mathbb{1}_j^{Up} = 0\} \times APS_{j,t-1}$	6.490**	5.944**	5.558*	5.956**	6.705**	6.227**	5.801**	6.172**
	(2.894)	(2.777)	(2.885)	(2.609)	(2.914)	(2.789)	(2.895)	(2.612)
$MP_e \times \{\mathbb{1}_j^{Up} = 1\} \times APS_{j,t-1}$	-4.827	-4.872	-5.088	-3.823	26.174	24.272	22.114	29.998
	(6.080)	(5.810)	(5.803)	(5.247)	(28.541)	(27.246)	(27.237)	(23.530)
$MP_e \times FPA_s$					0.401***	0.382***	0.366***	0.396***
					(0.132)	(0.135)	(0.135)	(0.119)
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	30172	26549	26549	26549	28043	24556	24556	24556

*Robust standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01.*

Notes: This table shows the estimation results under the empirical specification in Eq. (5), where the key independent variable $APS_{j,t-1}$ is the firm-level share of AI pricing jobs in all pricing jobs, lagged by one quarter. The term $\mathbb{1}_j^{Up}$ is a dummy indicator of upstream firms. The regression includes controls for the frequency of price adjustment (FPA_s) at the NAICS 6-digit industry level and its interactions with the monetary policy shocks. In addition, the regression includes the same set of firm-level controls as in the long-difference regressions, including (1) the lagged firm-level markup, the lagged firm-level share of AI workers, and the lagged share of pricing workers, and (2) the lagged firm-level characteristics. The regression also includes firm and event fixed effects.

Table 10 presents the result of our regression specification (5). The table shows that, for firms without AI pricing, an expansionary monetary policy shock raises their stock returns, with similar magnitudes for upstream firms and downstream firms. Second, adopting AI pricing significantly increases the sensitivity of stock returns to monetary policy shocks for downstream firms, but not for upstream firms. The differences in the stock return sensitivity for downstream adopters (relative to non-adopters) are economically meaningful. In particular, Column 8 of Table 10 shows that, moving from a downstream firm without AI pricing to one with $APS = 15\%$ (such as Amazon), the stock return responses would be topped up by one additional percentage point, comparable to that shown in Table 9.

5.4 Asymmetric Effects of Monetary Shocks

Table 11: Stock Return Response to Monetary Shocks: AI Pricing Share

	Allowing for Asymmetric Effects of Monetary Shocks (MP_e^+ Stands for Easing)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP_e^+	3.357***	3.243***	3.231***		3.364***	3.330***	3.258***	
	(0.147)	(0.155)	(0.156)		(0.326)	(0.331)	(0.333)	
MP_e^-	-1.821***	-1.996***	-1.860***		-2.588***	-2.726***	-2.715***	
	(0.110)	(0.117)	(0.120)		(0.239)	(0.247)	(0.254)	
$MP_e^+ \times APS_{j,t-1}$	-3.830	-3.665	-3.939	-2.633	-0.731	-0.727	-1.322	-1.072
	(3.038)	(3.083)	(3.100)	(2.800)	(6.430)	(6.130)	(6.168)	(5.566)
$MP_e^- \times APS_{j,t-1}$	-7.590***	-7.273***	-7.319***	-7.267***	-11.547***	-10.831**	-10.608**	-11.073***
	(2.146)	(2.234)	(2.267)	(2.049)	(4.470)	(4.285)	(4.406)	(3.978)
$MP_e^+ \times FPA_s$					0.663**	0.526*	0.549**	0.453*
					(0.266)	(0.276)	(0.276)	(0.250)
$MP_e^- \times FPA_s$					-0.180	-0.236	-0.195	-0.331*
					(0.207)	(0.208)	(0.210)	(0.189)
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	109802	96656	96656	96656	28043	24556	24556	24556

Robust standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01.

Notes: This table shows the estimation results under the empirical specification in Eq. (6), where the key independent variable $APS_{j,t-1}$ is the firm-level share of AI pricing jobs in all pricing jobs, lagged by one quarter. The regression includes controls for the frequency of price adjustment (FPA_s) at the NAICS 6-digit industry level and its interactions with the monetary policy shocks. In addition, the regression includes the same set of firm-level controls as in the long-difference regressions, including (1) the lagged firm-level markup, the lagged firm-level share of AI workers, and the lagged share of pricing workers and (2) the lagged firm-level characteristics. The regression also includes firm and event fixed effects.

Monetary policy easing and tightening may have asymmetric effects on the relative stock returns for firms adopting AI pricing. To examine this possibility, we estimate the empirical specification

$$\begin{aligned} R_{j,e} = \beta_0 + \beta_1^+ MP_e^+ + \beta_2^+ MP_e^+ \times APS_{j,t-1} + \beta_1^- MP_e^- + \beta_2^- MP_e^- \times APS_{j,t-1} \\ + \beta_3 APS_{j,t-1} + \beta_4 Z_{j,t-1} + \beta_5 FPA_s + \beta_6^+ MP_e^+ \times FPA_s + \beta_6^- MP_e^- \times FPA_s + \gamma_j + \epsilon_{je}, \end{aligned} \tag{6}$$

where $R_{j,e}$ denotes the daily stock return of firm j in the event date e, MP_e^+ denotes expansionary monetary policy shocks ($MP_e^+ = MP_e$ when MP_e is positive) and equals 0 otherwise, MP_e^- denotes contractionary shocks ($MP_e^- = -MP_e$ when MP_e is negative) and 0 otherwise. The remaining variables are the same as in Eq. (4).

Table 11 shows that, for firms without AI pricing, monetary expansion increases their stock returns, whereas monetary tightening reduces them. For firms that adopt AI pricing, the effects of monetary policy shocks are asymmetric. An expansionary monetary policy shock does not have significant effects on the stock returns of adopters (relative to nonadopters). In contrast, a contractionary monetary policy shock has a large and significantly negative effect on the relative stock returns of the adopters. This finding suggests that firms that adopt AI pricing are perceived as riskier, conditional on monetary policy contractions. One potential explanation is that firms that adopt AI pricing have higher markups (or profits) on average, so a contractionary monetary policy shock that leads to deviations from their average markups would reduce their market value. The results are qualitatively similar when we measure AI pricing adoptions using the adoption dummy (see Appendix D.3).

5.5 Robustness Checks

We conduct various robustness checks for the monetary shock results and present the results in Online Appendix D. We first show that the main results are robust when we measure AI pricing adoptions using the adoption dummy (see Table D1). Second, the results are also robust when we include the interactions of monetary policy shocks with each of the firm-level controls to alleviate concerns about potential confounding effects from predetermined firm characteristics other than AI pricing (see Table D2). Third, we also include additional analyses that incorporate interactions with control variables or exclude finance, information technology, and business services firms. Finally, we test the specifications using the non-orthogonalized monetary shocks from Bauer and Swanson (2023), and all the results remain robust.

6 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, a monopolist firm faces a demand function, which is a high-dimensional function of market characteristics. The firm uses pricing labor and algorithmic computing to learn about the demand function.[16] Learning about more aspects of the demand function allows the firm to price discriminate more effectively.

To make the model tractable, we abstract from dynamics and competition, although both dimensions are clearly important in an environment with information frictions. The model is static, with all intertemporal variations driven by the trend changes in the relative price of computing. In addition, our model focuses on the optimizing decisions of a monopolist, and thus abstracts from potential interactions between algorithmic pricing and competition, an important subject explored in other studies (Klein, 2021; Brown and MacKay, 2023). We use the model to study a different mechanism: how capital-labor complementarity incentivizes a firm to adopt AI pricing over time and how it affects firm performance measured by revenues 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 then use the model to explore the effects of aggregate demand shocks.

6.1 General Environment and Firm's Problem

General Environment We consider the pricing problem of monopolist firms. A firm sells a single good, which it produces at the 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 the firm's market size. Each submarket might represent individual buyers, consumer groups, regions, platforms, or other market disaggregation. We refer to submarkets as *individuals* for

[16] See the literature on information friction or information acquisition and price setting, i.e., Mankiw and Reis (2002), Maćkowiak and Wiederholt (2009), Woodford (2009), and Chen et al. (2020).

concreteness.

A 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:

$$d_j(p_j) = z_j - \eta p_j \tag{7}$$

where the slope η is common for all individuals, but the intercept z_j varies. Information frictions stem from imperfect knowledge of z_j.

Pricing Problem with Uncertain Demand We now describe how a monopolist sets prices 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

$$\max_{p_j \; j\in\mathcal{J}} \mathbb{E}\left[\int_{j\in\mathcal{J}} (p_j - \kappa)d_j(p_j)dj \,|\Omega\right] \tag{8}$$

Lemma 1 *Facing linear demand function (7), the firm's optimal price is*

$$p_j = \frac{\mathbb{E}\left[z_j|\Omega\right]}{2\eta} + \frac{\kappa}{2} \tag{9}$$

Proof: Appendix E.1.1

Thus, the optimal price set by the monopolist is a linear combination of the marginal cost and the intercept of the demand curve. With uncertain demand, unlike the special case with full information, the optimal price depends on the monopolist's conditional expectations of the intercept.

6.2 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.[17] 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.[18] 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.

[17] 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.

[18] 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.

Suppose firms observe factors $x(n)$ for all $n \in [0, N]$. 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 $R(N)$:

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

where $v \equiv \mathbb{V}\left[z_j\right]$. 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 differentiable.

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

$$\Phi \equiv \frac{(\bar{z}-\eta\kappa)^2}{4\eta} \tag{10}$$

Proof: Appendix E.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.

Ref. Comment 5: Extension with two wages is in the appendix.

The first order condition for basic pricing labor is

$$\mu\Phi\nu R'(N)F_b(L_a, L_b, C) = w \tag{11}$$

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

$$\mu\Phi\nu R'(N)F_a(L_a, L_b, C) = w \tag{12}$$

$$\mu\Phi\nu R'(N)F_c(L_a, L_b, C) = q \tag{13}$$

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:

$$F_a(L_a, L_b, C) = F_b(L_a, L_b, C) \tag{14}$$

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

$$\frac{F_a(L_a, L_b, C)}{F_c(L_a, L_b, C)} = \frac{w}{q} \tag{15}$$

6.3 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

$$F(L_a, L_b, C) = L_b^{\beta} + (AL_a)^{\alpha} C^{\gamma} \tag{16}$$

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 (16) 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

$$\mu\Phi(AL_a)^\alpha C^\gamma \geq wL_a + qC + \chi \tag{17}$$

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 (17) holds. We keep wages and productivity fixed, so this threshold is only a function of the computing price q. We assume that $1 > (\alpha + \gamma)$ which ensures that $\underline{\mu}(q)$ can be positive; if the returns to scale in AI pricing were too large, then all firms would always 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 E.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 (17); 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 facing a market of size μ. To connect the model to the empirical patterns of AI pricing adoptions, we interpret an aggregate economy as consisting of many such monopolist firms, each indexed by μ. We consider time variations in the aggregate economy as driven solely by changes in the computing price q. We also consider cross-section variations driven by the 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

$$\mathcal{S}_{AI}(q) = \int_{\mu} s_{AI}(\mu, q) dH(\mu)$$

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

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

6.4 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., $N < \frac{\nu}{\rho}$.

6.4.1 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 or AI productivity A increases.*

Proof: Appendix E.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. ■

6.4.2 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 E.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 E.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*

$$y = \mu \frac{\nu R(N) + \bar{z}^2 - \eta^2 \kappa^2}{4\eta} \tag{18}$$

Proof: Appendix E.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 E.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. ■

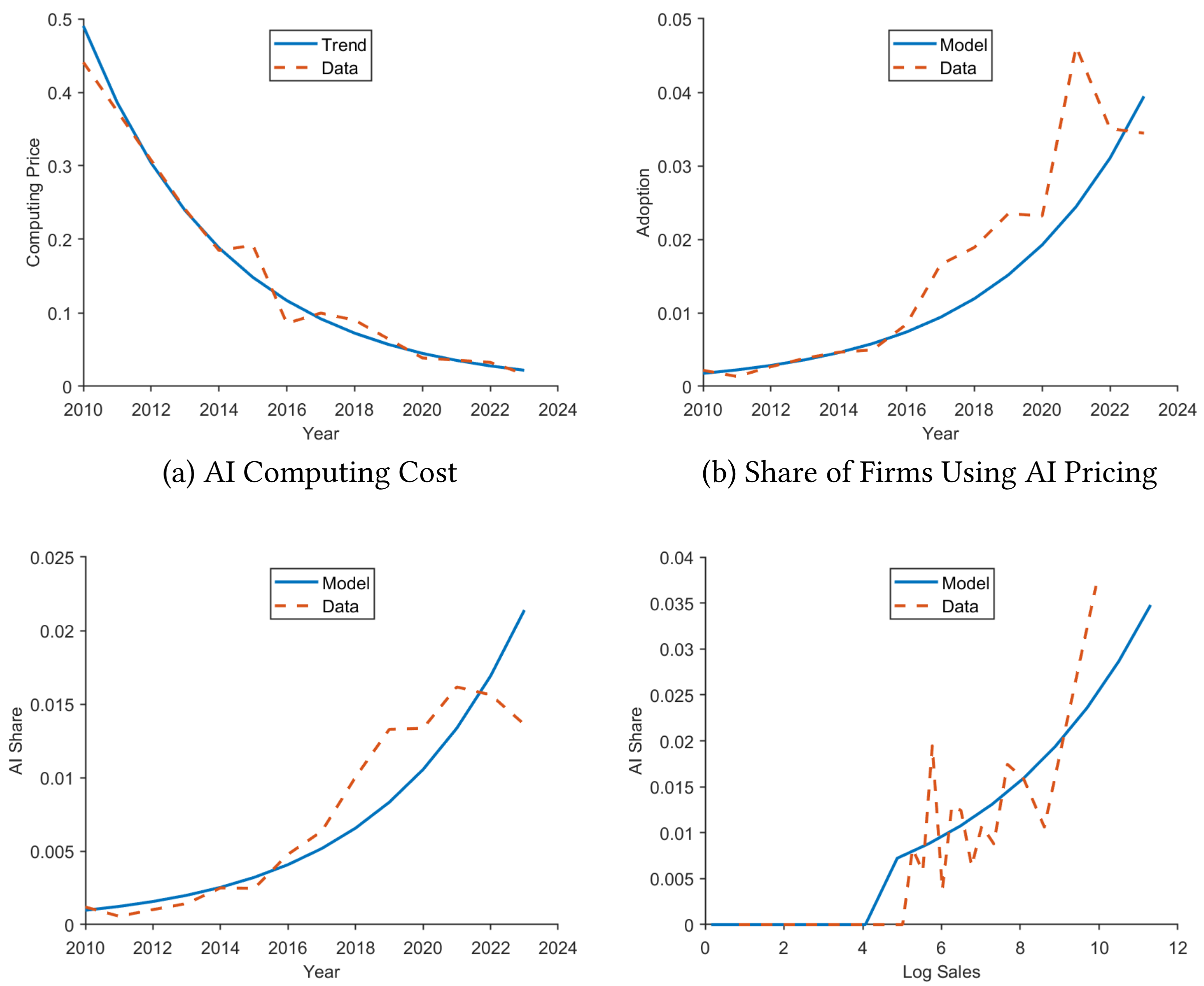
6.4.3 Model Behavior Compared to the Data

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) and 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. Then the fixed cost $\chi = 0.085$ roughly matches the adoption level in the cross-section.

Figure 5: 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 are also calculated from the Lightcast data, all described in Appendix E.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 $\beta = 0.75$, $\alpha = 0.6$, $\gamma = 0.2$, $A = 0.18$, $\Phi = 1$, $\rho = 1$, $\xi = 5$, $\chi = 0.085$, 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.

Figure 5 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 E.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.

In this exercise, the falling computing price q drives the time-series behavior. However, other relevant trends occurred during this period, and the model is helpful for considering their impacts as well. For example, markups have risen over this period (De Loecker, Eeckhout, and Unger, 2020; Döpper et al., 2025), and Proposition 4 implies that this would also increase the AI share of pricing labor over time. As another example, firms have accumulated greater amounts of data about their customers over this period (Veldkamp and Chung, 2024); if data increases the productivity of AI pricing A, then this trend will also increase the AI share of pricing labor over time (Lemma 4). Finally, changes to the pricing labor market will also affect the AI share; Appendix E.3 explores a model extension to address this in greater detail.

6.5 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 shocks conditional on AI pricing adoption and AI pricing share of labor in Section 5.

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 E.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 E.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 5.

7 Conclusion

We document the rise of 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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