Online Appendix to "The Rise of AI Pricing: Trends, Driving Forces, and Implications for Firm Performance"*

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A Supplements to The Rise of AI Pricing

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

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

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

A.2 Case Studies on Firms' AI Pricing Adoption

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

A.2.1 Uber

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

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

1. Early Dynamic Pricing (2010-2012): Uber implemented basic dynamic pricing to balance supply and demand early on. During periods of high demand (like holidays or inclement weather), prices would increase to incentivize more drivers to log on and meet demand. This early form of surge pricing was manually controlled and relatively simple, with limited data inputs. See www.uber.com/newsroom/take-a-walk-through-surge-pricing/.

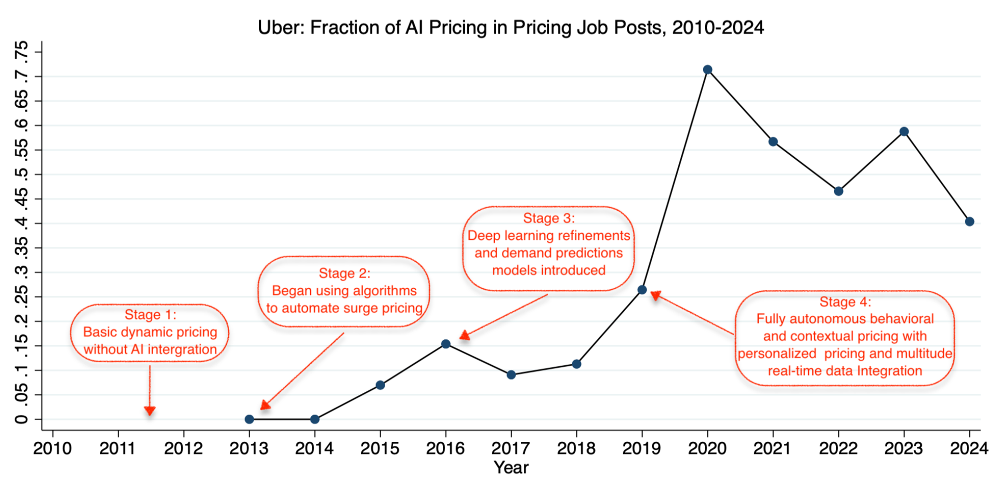
2. Algorithmic Surge Pricing (2013-2015): By the end of 2012, Uber began using algorithms to automate surge pricing. These algorithms monitored real-time data from rides, locations, and drivers to adjust prices. The system became more efficient, using basic machine learning models to analyze historical data, predict rider demand, and calculate the optimal price to balance the market dynamically. AI models started incorporating geospatial data

to predict specific regions where demand would spike. It could adjust city-wide pricing for specific neighborhoods or events, making the system more granular and localized. See www.uber.com/en-GB/newsroom/nye-2012-surge.

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

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

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



A.2.2 Amazon

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

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

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

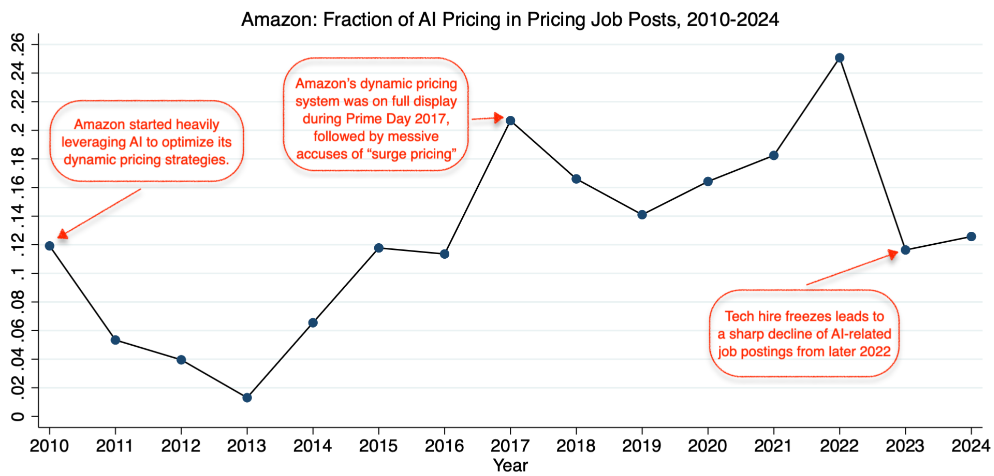
2. Introduction of Dynamic Pricing (2010-2015): Amazon developed more sophisticated dynamic pricing systems during this period. These systems used real-time data to adjust prices based on user activity, product popularity, and competitive market prices. AI started playing a larger role, allowing Amazon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

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

demand, adjusting prices before competitors could react.

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

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



A.2.3 JPMorgan Chase

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

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

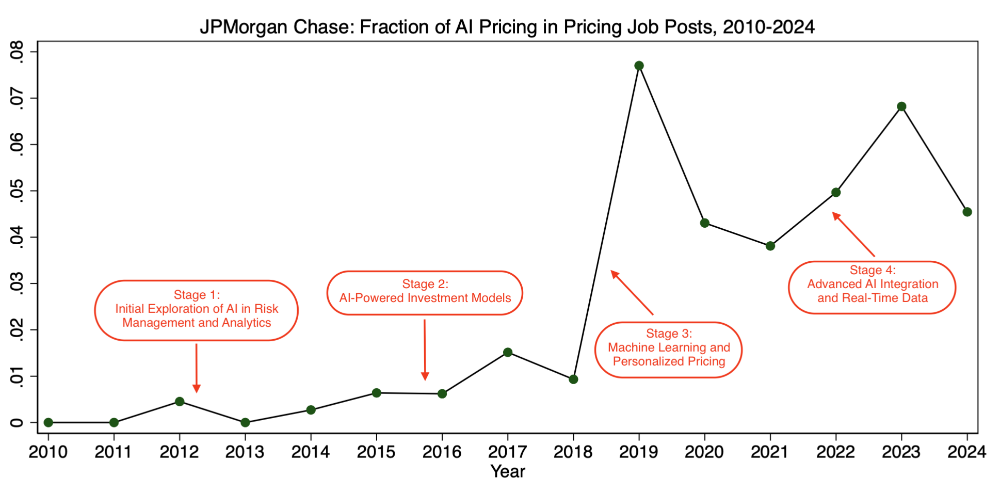
1. Initial Exploration of AI in Risk Management and Analytics (2010-2015): JPMorgan began leveraging AI primarily in risk management, credit analysis, and fraud detection. Pricing algorithms were still mostly rule-based; AI was used to analyze historical data and predict trends, laying the foundation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

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

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

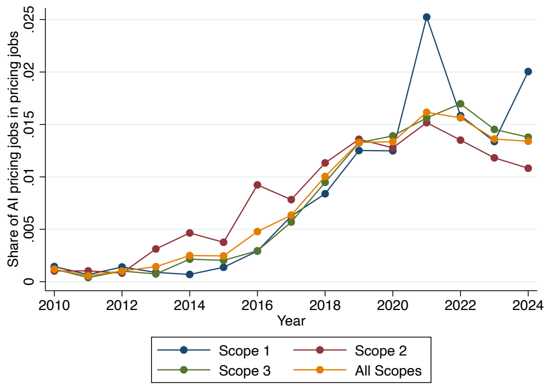
4. Advanced AI Integration and Real-Time Data (2020-Present): AI-driven pricing systems at JPMorgan now use real-time data across various services, including wealth management, investment products, and even day-to-day banking fees. AI models are capable of adjusting prices dynamically in response to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

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

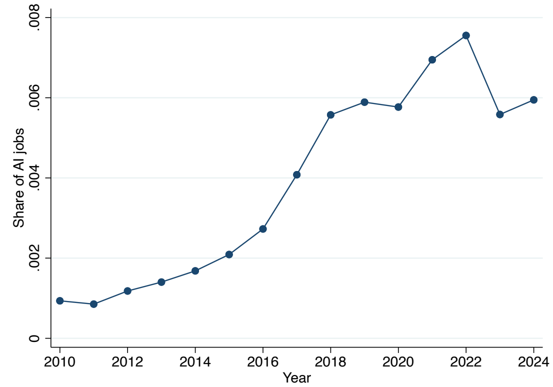


A.3 The Aggregate Trends in Alternative Measures

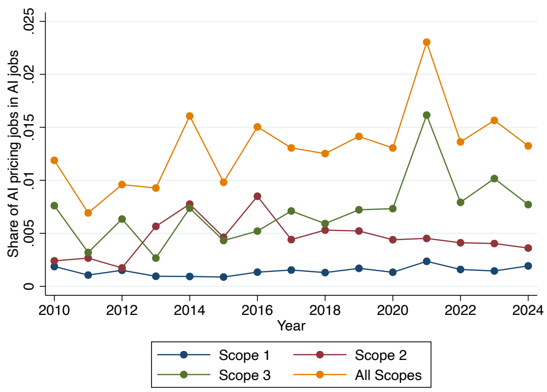
Figure A4: Aggregate Time Trends of AI Pricing, Pricing, and AI Jobs (Other Scopes)



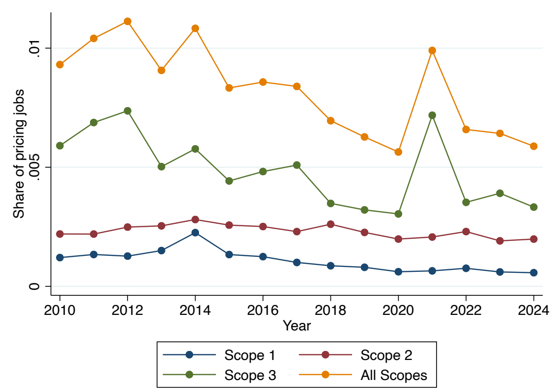
(a) Share of AI Pricing in Pricing Jobs



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

A.4 Leading Firms in AI Pricing

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

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

The list also suggests a wide range of applications of AI pricing across industries: Deloitte in professional services, Amazon in technology and e-commerce, and Uber in transportation and mobility. Additionally, RealReal and Wayfair, in the retail and e-commerce sectors, show high percentages of AI pricing jobs within their pricing roles at 43.6% and 25.7%, respectively. This indicates their strong reliance on AI to enhance pricing strategies in highly competitive and dynamic markets. Traditional financial institutions like JPMorgan Chase and Wells Fargo are also on the list despite having relatively lower shares of AI pricing jobs at 2.8% and 3.3%, respectively. Notably, Rippling, a cloud-based human resources (HR) software company, stands out with exceptionally high shares of AI pricing jobs, at 74.1% of AI jobs and 94.5% of pricing jobs, signaling a deep integration of AI in their business of potential wage-setting services provided to their customers.[1] This heterogeneity reveals the substantial applicability and emerging stages of AI adoption in pricing across industries and firms.

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

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

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

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

A.5 Leading Firms in AI Pricing in Alternative Measures

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

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

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

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

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

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

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

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

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

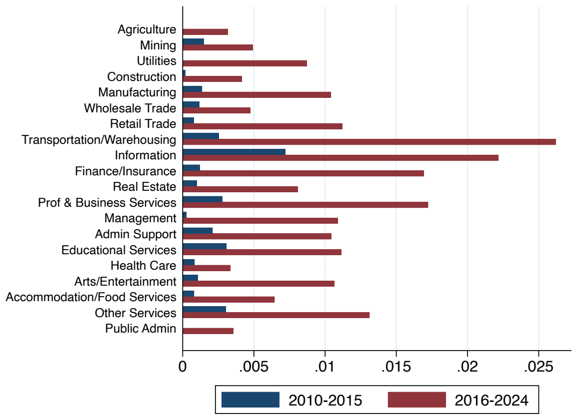
Company	No. AI pricing jobs	AI Pricing/AI Jobs	AI Pricing/Pricing Jobs
Amazon	668	0.9%	17.7%
Deloitte	632	2.6%	4.6%
Uber	373	11.9%	49.4%
The RealReal	311	6.3%	47.2%
Johnson & Johnson	296	4.1%	6.4%
CyberCoders	293	0.8%	3.1%
USAA	263	7.2%	7.4%
JPMorgan Chase	233	1.8%	3.2%
General Motors	190	2.5%	7.3%
Wells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

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

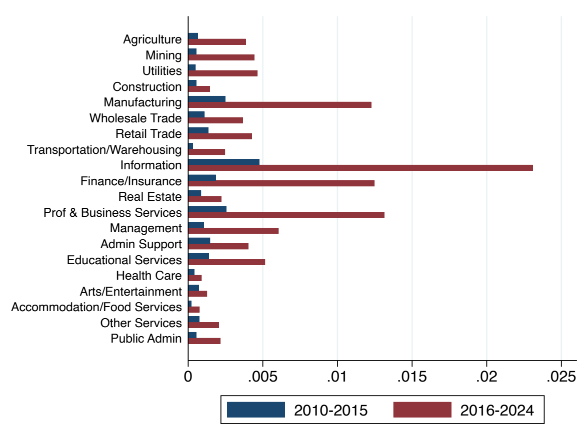
A.6 Variations Across Industries of AI Pricing

The below figure includes two additional plots as an addition to Figure 2 in the paper.

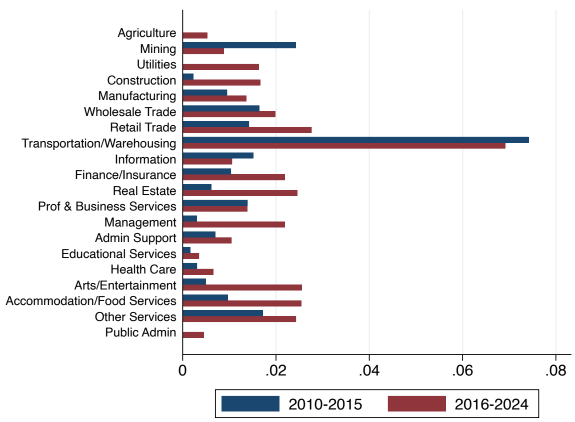
Figure A5: Variations Across Two Digit Industry Sector



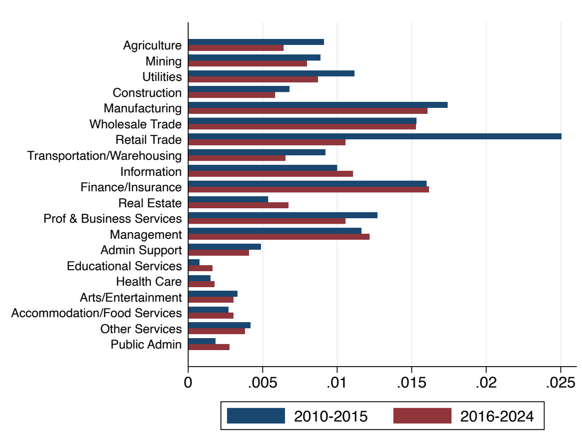
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Jobs in All Jobs



(c) Share of AI Pricing in AI Jobs

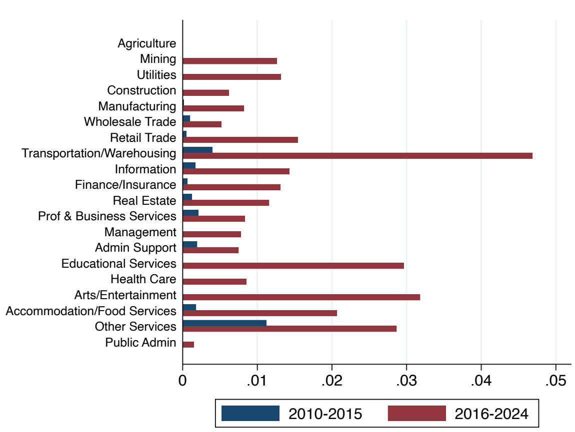


(d) Share of Pricing Jobs in All Jobs

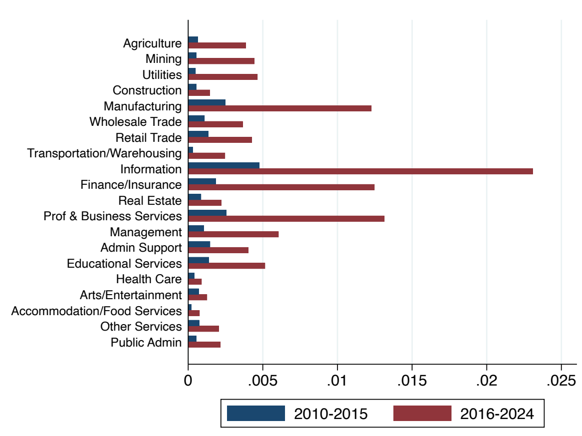
Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs, measured in different shares and scopes for two periods: 2010-2015 and 2016-2024. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022)'s narrow category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

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

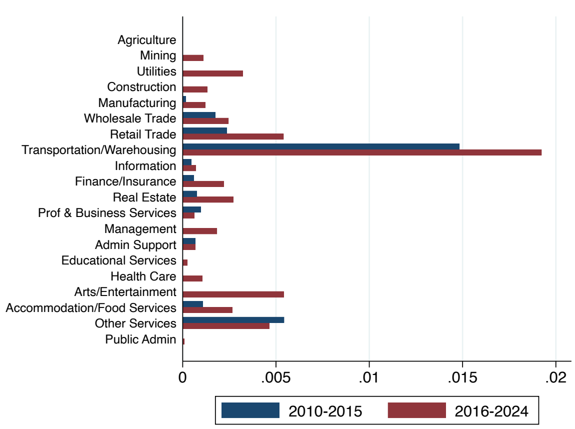
Figure A6: Variations Across Two Digit Industry Sector (Scope 1)



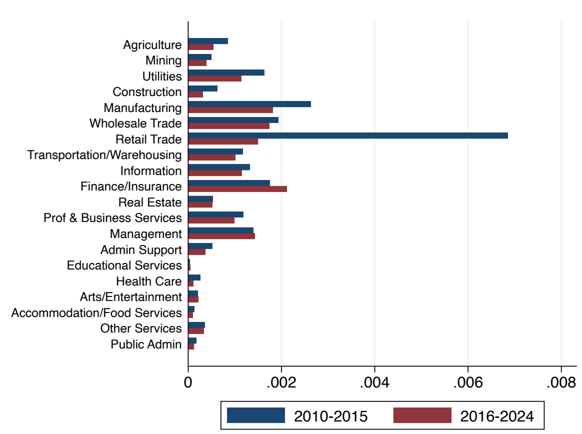
(a) Share of AI Pricing in Pricing Jobs (Scope 1)



(b) Share of AI Jobs



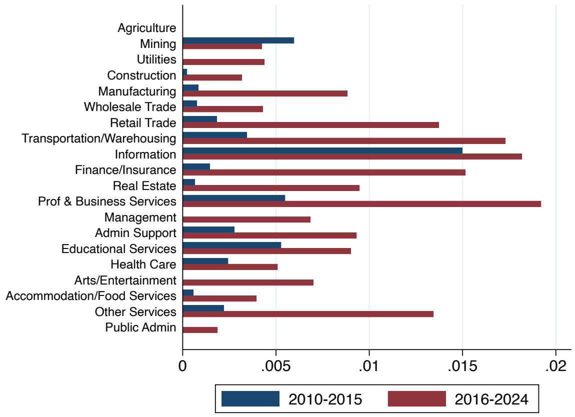
(c) Share of AI Pricing in AI Jobs (Scope 1)



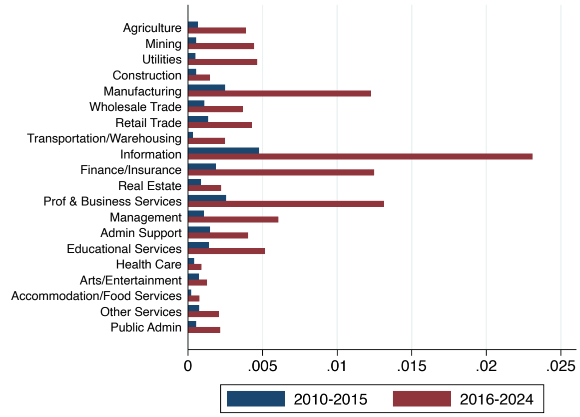
(d) Share of Pricing Jobs (Scope 1)

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

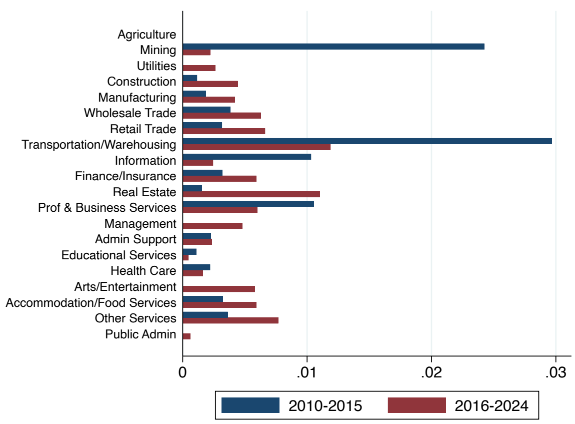
Figure A7: Variations Across Two Digit Industry Sector (Scope 2)



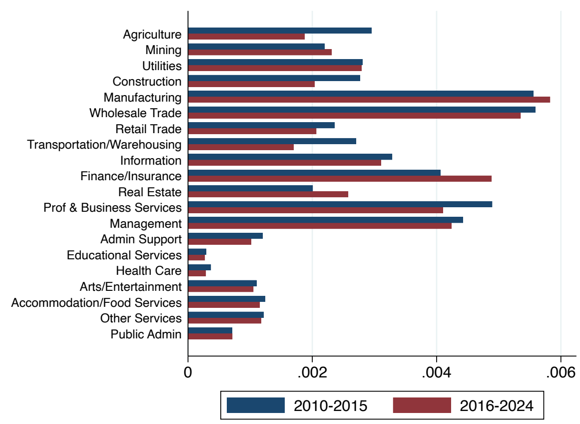
(a) Share of AI Pricing in Pricing Jobs (Scope 2)



(b) Share of AI Jobs



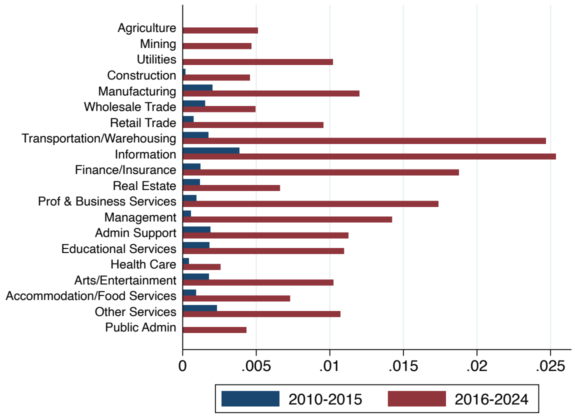
(c) Share of AI Pricing in AI Jobs (Scope 2)



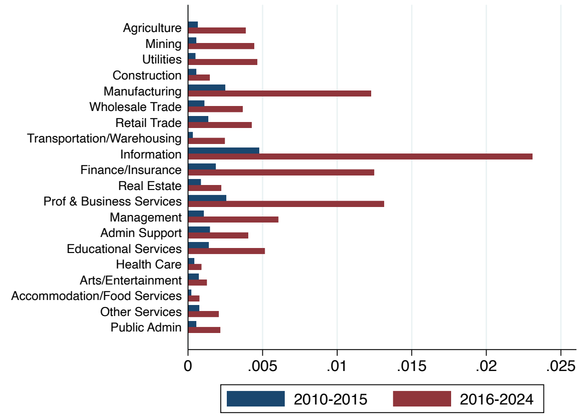
(d) Share of Pricing Jobs (Scope 2)

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

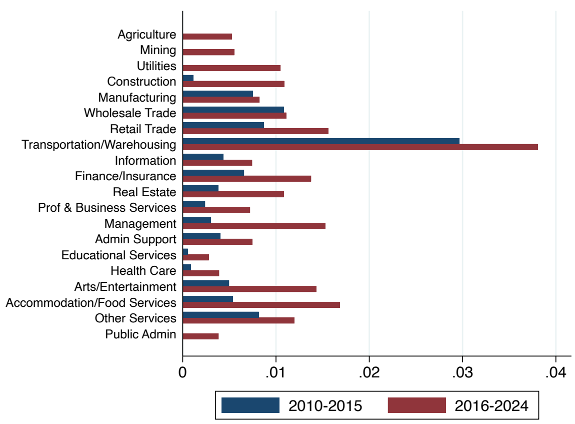
Figure A8: Variations Across Two Digit Industry Sector (Scope 3)



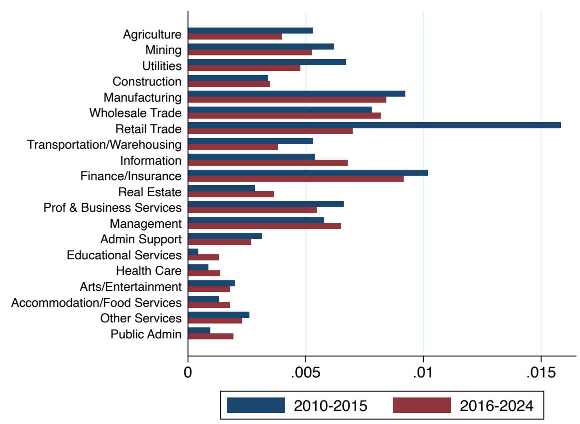
(a) Share of AI Pricing in Pricing Jobs (Scope 3)



(b) Share of AI Jobs



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



(d) Share of Pricing Jobs (Scope 3)

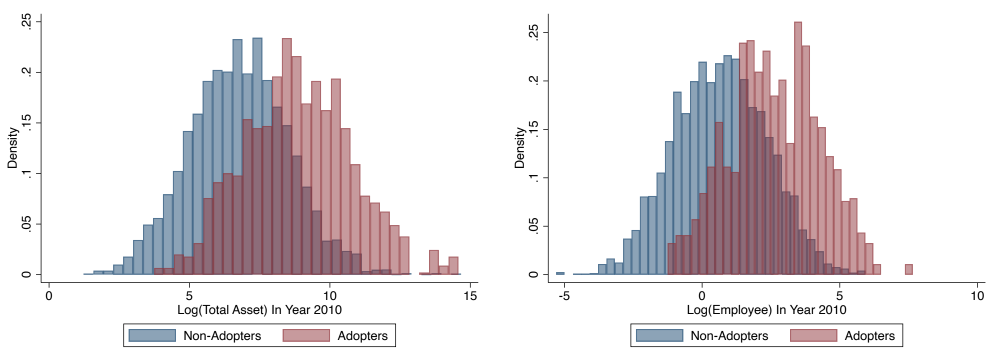
Notes: This figure plots the across-industry variations of AI pricing, pricing, and AI jobs, measured in different shares and scopes for two periods: 2010-2015 and 2016-2024. The data source is Lightcast job postings. AI job postings are measured following exactly Acemoglu et al. (2022)'s narrow category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

B Supplements to Firm-level Determinants

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

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

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



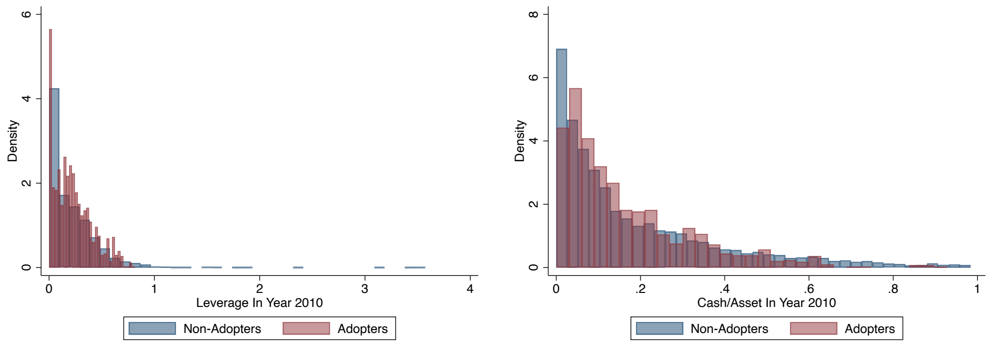
(a) Log Total Asset Distribution (b) Log Employee Distribution

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

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

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

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

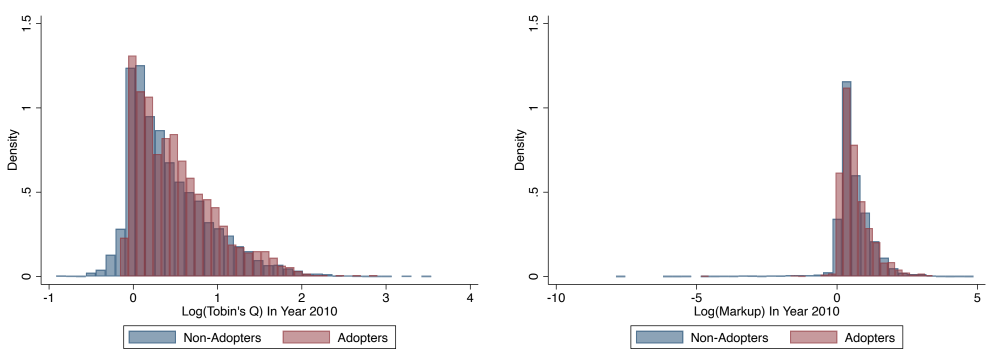


(a) Leverage Distribution (b) Cash/Asset Distribution

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

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

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



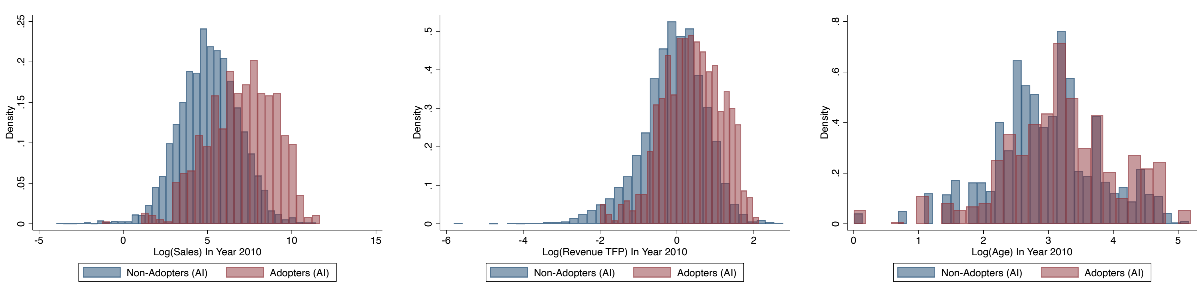
(a) Log Tobin's Q Distribution (b) Log Markup Distribution

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

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

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

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



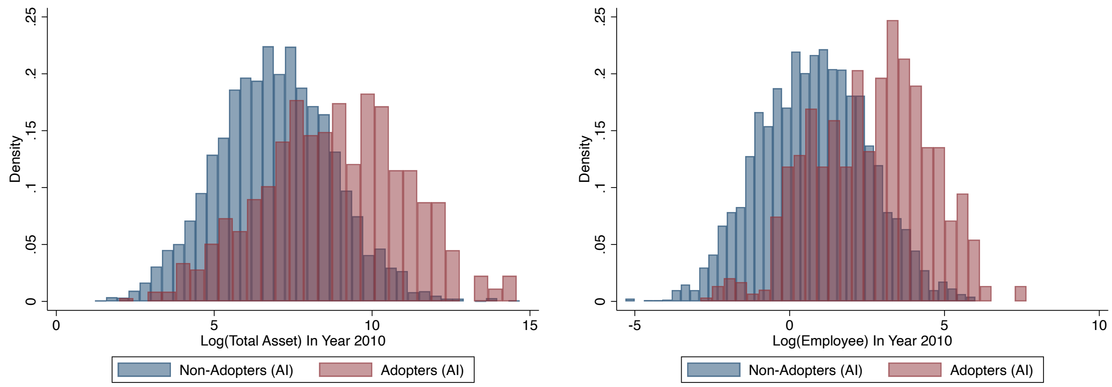
(a) Size Distribution (b) TFP Distribution (c) Age Distribution

Notes: These figures compare AI adoption to the AI pricing adoption distribution in Figure 4. An AI adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 1$) is a firm j that posted at least one AI job since the beginning of our data sample until 2024Q1; Non-Adopter ($\mathbb{1}^{AI}_{j,2024Q1} = 0$) is a firm j that never posted AI job since the beginning of our data sample until 2024Q1.

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

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

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

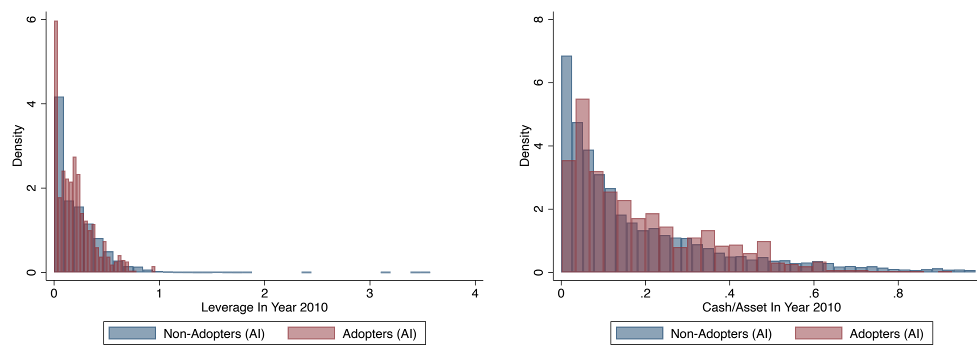


(a) Log Total Asset Distribution

(b) Log Employee Distribution

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

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



(a) Leverage Distribution

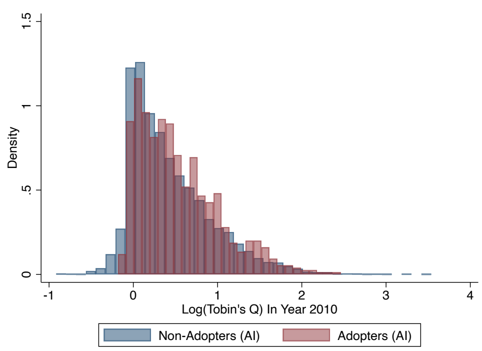
(b) Cash/Asset Distribution

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

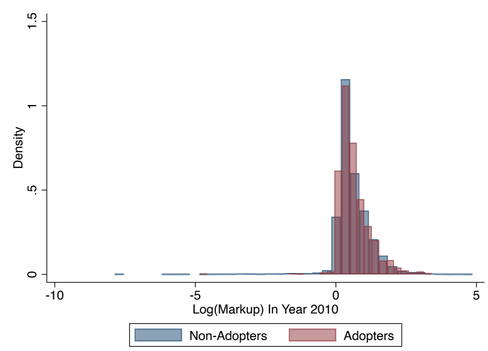
concentration of firms at lower leverage levels. However, AI adopters (in red) show a slightly higher density at very low leverage levels. Graph (b) displays the cash/asset distribution, where both groups again show similar overall patterns, with a high concentration of firms having lower cash/asset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

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

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



(a) Log Tobin's Q Distribution



(b) Log Markup Distribution

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

B.3 Firm-level Determinants of AI Pricing Adoption (Probit Regression)

Table B1 presents the probit regression results for the dependent variable, the adoption dummy $\mathbb{1}^{AP}_{j,2024Q1}$. Standard errors are in parentheses. Significance: * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The probit regression results are generally consistent with those in the main paper, indicating that size, productivity, and R&D intensity in 2010 are positively correlated with AI pricing adoption from 2010 to 2024 Q1.

Table B1: Firm-level Determinants of AI Pricing Adoption (Probit Regression)

	AI Pricing Adopter Dummy Indicator, 2010-2015Q4 ($\mathbb{1}^{AP}_{j,2015Q4} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.462***									0.511***
	(0.013)									(0.018)
Log TFP 2010		0.502***								0.132***
		(0.027)								(0.042)
Log Age 2010			0.128***							-0.057**
			(0.022)							(0.026)
Tobin's Q 2010				0.041***						0.080***
				(0.012)						(0.017)
Log Markup 2010					0.071**					0.075
					(0.029)					(0.060)
R&D/Sales 2010						-0.005				1.745***
						(0.007)				(0.308)
ROA 2010							-1.724***			-0.088
							(0.546)			(0.792)
Cash/Assets 2010								-0.484***		-0.206
								(0.103)		(0.183)
Debt/Assets 2010									0.288***	-0.226**
									(0.080)	(0.114)
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	7748	7040	7278	7765	7728	7777	7756	7767	7279	6316

B.4 Firm-level Determinants of AI Pricing Adoption in Sub-periods

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

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

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

where j represents firms, q is one of the four quarters, and s refers to two-digit NAICS sectors. The dependent variables are firm j's AI pricing adoption indicator, which equals one if the firm posts at least one AI pricing job post within the subperiod. The independent variables represents firm j's characteristic in quarter q of 2010 or 2016, for $q = Q1, Q2, Q3, Q4$. The characteristics examined include logged sales, logged TFP, logged age, Tobin's Q, logged markup, the ratio of R&D to sales, ROA, cash-to-assets ratio, and debt-to-assets ratio, all winsorized at the top and bottom 1% at the year quarter frequency.[2] We also include industry fixed effects (γ_s) and quarter fixed effects (δ_q) to control for unobserved heterogeneity.

Sub-period 1: 2010-2015 Tables B2, B3, and B4 report the results of sub-period 1 for dependent variables $\{\mathbb{1}^{AP}_{j,2015Q4}, APN_{j,2015Q4}, APS_{j,2015Q4}\}$, respectively. Standard errors are in parentheses. Significance: * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The sub-period results are generally consistent with the results in the main paper.

Sub-period 2: 2016-2024 Tables B5, B6, and B7 report the results of sub-period 2 for dependent variables $\{\mathbb{1}^{AP}_{j,2024Q1}, APN_{j,2024Q1}, APS_{j,2024Q1}\}$, respectively. Standard errors are in parentheses. Significance: * p<.1, ** p<0.05, *** p<0.01. All independent variables are winsorized at the top and bottom 1% at the year quarter frequency. Industry fixed effects are controlled at the two-digit NAICS level. The sub-period results are generally consistent with the results in the main paper.

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

Table B2: Firm-level Determinants of AI Pricing Adoption

	AI Pricing Adopter Dummy Indicator, 2010-2015Q4 ($\mathbb{1}^{AP}_{j,2015Q4} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.022***									0.023***
	(0.001)									(0.002)
Log TFP 2010		0.032***								0.016***
		(0.003)								(0.004)
Log Age 2010			0.013***							0.004
			(0.003)							(0.003)
Tobin's Q 2010				-0.000						-0.004*
				(0.001)						(0.002)
Log Markup 2010					0.002					0.004
					(0.003)					(0.006)
R&D/Sales 2010						-0.000				0.063**
						(0.000)				(0.029)
ROA 2010							-0.065*			0.035
							(0.039)			(0.050)
Cash/Assets 2010								-0.006		0.022
								(0.011)		(0.017)
Debt/Assets 2010									0.010	-0.011
									(0.009)	(0.011)
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	0.067	0.035	0.021	0.017	0.017	0.017	0.017	0.017	0.014	0.072

Table B3: Firm-level Determinants of Cumulative AI Pricing Job Postings

	Total AI pricing job Postings, 2010-2015Q4 ($APN_{j,2015Q4}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.220***									0.198***
	(0.027)									(0.033)
Log TFP 2010		0.456***								0.238***
		(0.069)								(0.082)
Log Age 2010			0.076							0.063
			(0.062)							(0.058)
Tobin's Q 2010				0.129***						0.022
				(0.036)						(0.041)
Log Markup 2010					0.048					0.008
					(0.078)					(0.127)
R&D/Sales 2010						0.000				1.222*
						(0.003)				(0.625)
ROA 2010							-0.537			0.051
							(0.931)			(1.078)
Cash/Assets 2010								0.298		-0.156
								(0.265)		(0.361)
Debt/Assets 2010									0.290	0.179
									(0.189)	(0.237)
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	0.019	0.016	0.012	0.012	0.010	0.010	0.010	0.010	0.005	0.018

Table B4: Firm-level Determinants of Cumulative AI Pricing Job Postings Intensity

	Total AI pricing job Postings/Total Pricing Job Postings, 2010Q1-2015Q4 ($APS_{j,2015Q4}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	-0.001*									-0.001***
	(0.000)									(0.001)
Log TFP 2010		0.003***								0.005***
		(0.001)								(0.001)
Log Age 2010			-0.003***							-0.003***
			(0.001)							(0.001)
Tobin's Q 2010				-0.000						-0.001**
				(0.000)						(0.001)
Log Markup 2010					0.001					-0.004**
					(0.001)					(0.002)
R&D/Sales 2010						0.000				0.030***
						(0.000)				(0.010)
ROA 2010							-0.008			-0.025
							(0.019)			(0.026)
Cash/Assets 2010								0.006*		-0.003
								(0.004)		(0.006)
Debt/Assets 2010									0.001	0.004
									(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	5601	5267	5320	5607	5588	5611	5601	5607	5297	4782
adj. R^2	0.002	0.003	0.004	0.002	0.002	0.002	0.002	0.002	0.002	0.009

Table B5: Firm-level Determinants of AI Pricing Adoption

	AI Pricing Adopter Dummy Indicator, 2016-2024Q1 ($\mathbb{1}^{AP}_{j,2024Q1} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2016	0.081***									0.113***
	(0.002)									(0.003)
Log TFP 2016		0.100***								0.012*
		(0.005)								(0.007)
Log Age 2016			0.037***							0.001
			(0.005)							(0.005)
Tobin's Q 2016				0.023***						0.021***
				(0.003)						(0.003)
Log Markup 2016					0.011**					0.036***
					(0.004)					(0.008)
R&D/Sales 2016						-0.000				0.034***
						(0.000)				(0.008)
ROA 2016							-0.341***			0.398***
							(0.066)			(0.115)
Cash/Assets 2016								-0.063***		0.124***
								(0.020)		(0.031)
Debt/Assets 2016									0.094***	-0.055***
									(0.017)	(0.020)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	9179	8004	8641	9324	9160	9338	9325	9328	8734	7228
adj. R^2	0.197	0.063	0.030	0.034	0.026	0.026	0.029	0.027	0.028	0.253

Table B6: Firm-level Determinants of Cumulative AI Pricing Job Postings

	Total AI pricing job Postings, 2016-2024Q1($APN_{j,2024Q1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2016	3.139***									5.028***
	(0.157)									(0.268)
Log TFP 2016		4.114***								0.229
		(0.450)								(0.622)
Log Age 2016			0.958**							-0.482
			(0.379)							(0.447)
Tobin's Q 2016				0.984***						0.828***
				(0.208)						(0.311)
Log Markup 2016					0.148					1.076
					(0.357)					(0.774)
R&D/Sales 2016						-0.001				1.332*
						(0.003)				(0.790)
ROA 2016							-10.167*			11.496
							(5.279)			(10.781)
Cash/Assets 2016								1.215		12.525***
								(1.569)		(2.864)
Debt/Assets 2016									1.736	-4.511**
									(1.387)	(1.885)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	9179	8004	8641	9324	9160	9338	9325	9328	8734	7228
adj. R^2	0.054	0.022	0.014	0.015	0.013	0.013	0.013	0.013	0.013	0.075

Table B7: Firm-level Determinants of Cumulative AI Pricing Job Postings Intensity

	Total AI pricing job Postings/Total Pricing Job Postings, 2016Q1-2024Q4 ($APS_{j,2024Q1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2016	0.001***									0.002***
	(0.000)									(0.001)
Log TFP 2016		0.004***								0.002*
		(0.001)								(0.001)
Log Age 2016			-0.001*							-0.002*
			(0.001)							(0.001)
Tobin's Q 2016				0.002***						0.001*
				(0.000)						(0.001)
Log Markup 2016					-0.001					-0.003**
					(0.001)					(0.001)
R&D/Sales 2016						-0.000				0.000
						(0.000)				(0.005)
ROA 2016							0.021			0.042*
							(0.015)			(0.023)
Cash/Assets 2016								0.013***		0.024***
								(0.003)		(0.006)
Debt/Assets 2016									0.001	0.001
									(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	7449	6804	7127	7531	7438	7544	7535	7535	7097	6192
adj. R^2	0.015	0.018	0.015	0.016	0.014	0.014	0.014	0.016	0.016	0.029

C Supplements to Firm Performance in Long-differences

C.1 Firm Performance: Excluding Financial and Utility Firms

Table C1: AI Pricing and Firm Performance: Long-differences, Excluding Finance & Utility

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	3.236***	3.209***	2.806***	2.720***	3.568***	3.646***	0.635**	0.967***
	(0.537)	(0.501)	(0.467)	(0.448)	(0.550)	(0.546)	(0.252)	(0.162)
Share of AI		-0.637		-0.935		-1.034		-1.082***
		(0.741)		(0.646)		(0.807)		(0.240)
Share of Pricing		0.140		0.298		0.288		0.285***
		(0.337)		(0.301)		(0.366)		(0.109)
Log Sales		-0.102***		-0.146***		-0.131***		0.016***
		(0.010)		(0.010)		(0.011)		(0.003)
Log TFP		0.045**		0.170***		0.113***		-0.078***
		(0.022)		(0.020)		(0.024)		(0.007)
R&D/Sales		1.578***		1.078***		1.041***		0.225***
		(0.190)		(0.175)		(0.207)		(0.062)
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	3074	2986	2760	2696	3080	2987	3074	2986
adj. R^2	0.051	0.125	0.102	0.218	0.063	0.129	0.018	0.063

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.

C.2 Firm Performance: Excluding Information Technology Firms

Table C2: AI Pricing and Firm Performance: Long-differences, Excluding IT

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.142***	1.071***	1.001***	0.876***	0.935***	0.999***	0.176	0.149
	(0.333)	(0.303)	(0.285)	(0.267)	(0.338)	(0.325)	(0.166)	(0.115)
Share of AI		-0.542		-0.790		-0.884		-0.572**
		(0.692)		(0.607)		(0.741)		(0.261)
Share of Pricing		0.113		0.327		0.145		0.018
		(0.193)		(0.251)		(0.207)		(0.073)
Log Sales		-0.103***		-0.116***		-0.133***		0.005
		(0.009)		(0.008)		(0.010)		(0.003)
Log TFP		0.021		0.150***		0.077***		-0.082***
		(0.020)		(0.018)		(0.021)		(0.007)
R&D/Sales		1.790***		1.422***		1.192***		0.340***
		(0.186)		(0.171)		(0.199)		(0.070)
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	3737	3501	3445	3240	3748	3505	3737	3501
adj. R^2	0.067	0.155	0.089	0.188	0.046	0.124	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.

C.3 Firm Performance: Excluding Professional & Business Services Firms

Table C3: AI Pricing and Firm Performance: Long-differences, Excluding Business Services

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.292***	1.288***	1.036***	0.977***	1.224***	1.322***	0.237	0.231*
	(0.342)	(0.314)	(0.296)	(0.278)	(0.353)	(0.341)	(0.173)	(0.126)
Share of AI		-0.604		-0.594		-0.652		-0.839***
		(0.734)		(0.644)		(0.799)		(0.294)
Share of Pricing		0.089		0.223		0.079		-0.056
		(0.191)		(0.239)		(0.207)		(0.076)
Log Sales		-0.104***		-0.122***		-0.138***		0.008**
		(0.009)		(0.008)		(0.010)		(0.004)
Log TFP		0.048**		0.176***		0.117***		-0.092***
		(0.020)		(0.018)		(0.022)		(0.008)
R&D/Sales		1.547***		1.208***		0.995***		0.322***
		(0.181)		(0.167)		(0.197)		(0.073)
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	3855	3620	3538	3334	3866	3624	3855	3620
adj. R^2	0.066	0.148	0.088	0.189	0.051	0.127	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.

C.4 Firm Performance: Excluding Finance, IT, and PBS

Table C4: AI Pricing and Firm Performance: Long-differences, Excluding Fin, IT, PBS

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	3.810***	3.962***	3.238***	3.356***	3.773***	4.012***	0.414	0.738***
	(0.594)	(0.547)	(0.506)	(0.486)	(0.591)	(0.582)	(0.278)	(0.157)
Share of AI		-1.276		-1.266*		-1.333		-1.250***
		(0.779)		(0.688)		(0.829)		(0.223)
Share of Pricing		0.378		0.486		0.551		0.575***
		(0.371)		(0.338)		(0.394)		(0.106)
Log Sales		-0.104***		-0.147***		-0.138***		0.011***
		(0.011)		(0.011)		(0.012)		(0.003)
Log TFP		0.017		0.141***		0.095***		-0.061***
		(0.024)		(0.022)		(0.025)		(0.007)
R&D/Sales		1.804***		1.318***		1.241***		0.241***
		(0.202)		(0.187)		(0.215)		(0.058)
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	2638	2553	2389	2328	2644	2554	2638	2553
adj. R^2	0.056	0.139	0.113	0.226	0.064	0.139	0.016	0.070

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.

C.5 Firm Performance: Excluding Largest Firms by Top 1%, 5%, or 10%

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

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

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.247***	1.128***	1.075***	0.890***	1.200***	1.192***	0.266	0.263**
	(0.334)	(0.307)	(0.288)	(0.271)	(0.346)	(0.335)	(0.168)	(0.122)
Share of AI		-0.355		-0.623		-0.698		-0.639**
		(0.700)		(0.611)		(0.764)		(0.278)
Share of Pricing		0.070		0.208		0.082		-0.051
		(0.191)		(0.237)		(0.208)		(0.076)
Log Sales		-0.107***		-0.120***		-0.137***		0.008**
		(0.009)		(0.009)		(0.010)		(0.004)
Log TFP		0.049**		0.175***		0.108***		-0.092***
		(0.020)		(0.018)		(0.021)		(0.008)
R&D/Sales		1.543***		1.173***		0.986***		0.320***
		(0.180)		(0.166)		(0.196)		(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	3936	3703	3602	3400	3947	3707	3936	3703
adj. R^2	0.065	0.143	0.087	0.182	0.048	0.117	0.018	0.058

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.

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

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.105***	0.915***	0.841***	0.600**	1.077***	0.989***	0.240	0.206
	(0.341)	(0.314)	(0.290)	(0.273)	(0.353)	(0.343)	(0.175)	(0.126)
Share of AI		-0.470		-0.748		-0.801		-0.622**
		(0.707)		(0.610)		(0.775)		(0.283)
Share of Pricing		0.023		0.146		0.040		-0.057
		(0.193)		(0.239)		(0.211)		(0.077)
Log Sales		-0.104***		-0.117***		-0.128***		0.006
		(0.011)		(0.010)		(0.012)		(0.004)
Log TFP		0.043**		0.171***		0.096***		-0.094***
		(0.020)		(0.018)		(0.022)		(0.008)
R&D/Sales		1.578***		1.218***		1.053***		0.338***
		(0.184)		(0.168)		(0.202)		(0.074)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3675	3455	3354	3157	3686	3459	3675	3455
adj. R^2	0.069	0.139	0.088	0.175	0.054	0.110	0.021	0.061

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \delta_q + \epsilon_j$, 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.

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

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.184***	0.967***	0.973***	0.699**	1.310***	1.192***	0.351*	0.312**
	(0.361)	(0.334)	(0.301)	(0.284)	(0.372)	(0.364)	(0.185)	(0.130)
Share of AI		-0.420		-0.689		-0.768		-0.643**
		(0.729)		(0.614)		(0.796)		(0.284)
Share of Pricing		0.042		0.171		0.067		-0.063
		(0.201)		(0.246)		(0.219)		(0.078)
Log Sales		-0.085***		-0.095***		-0.113***		0.009*
		(0.013)		(0.011)		(0.014)		(0.005)
Log TFP		0.040*		0.183***		0.104***		-0.093***
		(0.022)		(0.019)		(0.024)		(0.008)
R&D/Sales		1.622***		1.291***		1.106***		0.359***
		(0.192)		(0.172)		(0.210)		(0.075)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3345	3142	3032	2852	3356	3146	3345	3142
adj. R^2	0.057	0.114	0.066	0.143	0.042	0.087	0.023	0.061

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \Gamma Z_{j,t1} + \gamma_s + \delta_q + \epsilon_j$, 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.

C.6 Firm Performance: Controlling for Changes in Other Shares

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

	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup	Δ Log Sales	Δ Log Employment	Δ Log Assets	Δ Log Markup
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.106***	0.848***	1.161***	0.247**	1.138***	0.877***	1.198***	0.259**
	(0.304)	(0.268)	(0.332)	(0.120)	(0.305)	(0.268)	(0.332)	(0.121)
$\Delta AIS_{j,[2010,2023]}$	2.696***	2.497***	3.118***	1.059***				
	(0.732)	(0.644)	(0.798)	(0.290)				
$\Delta PS_{j,[2010,2023]}$					-0.402	-0.527	-0.671	-0.190
					(0.651)	(0.599)	(0.709)	(0.258)
Share of AI	-1.403*	-1.587**	-1.897**	-1.034***	-0.380	-0.648	-0.717	-0.632**
	(0.751)	(0.655)	(0.818)	(0.297)	(0.698)	(0.609)	(0.761)	(0.276)
Share of Pricing	0.070	0.240	0.082	-0.049	0.098	0.311	0.130	-0.036
	(0.190)	(0.236)	(0.206)	(0.075)	(0.196)	(0.253)	(0.213)	(0.078)
Log Sales	-0.106***	-0.123***	-0.136***	0.008**	-0.103***	-0.121***	-0.133***	0.009***
	(0.009)	(0.008)	(0.010)	(0.003)	(0.009)	(0.008)	(0.010)	(0.003)
Log TFP	0.035*	0.164***	0.093***	-0.097***	0.047**	0.176***	0.107***	-0.092***
	(0.020)	(0.018)	(0.021)	(0.008)	(0.019)	(0.018)	(0.021)	(0.008)
R&D/Sales	1.446***	1.092***	0.871***	0.274***	1.560***	1.200***	1.004***	0.319***
	(0.181)	(0.167)	(0.197)	(0.072)	(0.179)	(0.165)	(0.195)	(0.071)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	3583	3293	3587	3583	3583	3293	3587	3583
adj. R^2	0.186	0.230	0.202	0.056	0.183	0.228	0.200	0.054

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \gamma\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_j$, 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. And $\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\}$ measures the changes in AI share and Pricing share in the same fashion. Both the changes in AI share and Pricing share are orthogonal to $\Delta APS_{j,[t1,t2]}$, so AI pricing jobs are not picked up in either of the measures. We omit 2024Q1 for potential seasonality. $Z_{j,t1}$ 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.

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

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.070***	1.107***	0.860***	0.850***	1.017***	1.163***	0.245	0.247**
	(0.332)	(0.304)	(0.286)	(0.268)	(0.344)	(0.332)	(0.167)	(0.120)
$\Delta AIS_{j,[2010,2023]}$	3.099***	2.697***	3.333***	2.499***	3.044***	3.121***	0.416	1.060***
	(0.721)	(0.732)	(0.620)	(0.644)	(0.745)	(0.798)	(0.362)	(0.290)
$\Delta PS_{j,[2010,2023]}$	-1.058	-0.409	-0.589	-0.534	-1.497**	-0.679	-0.534	-0.192
	(0.670)	(0.650)	(0.581)	(0.598)	(0.692)	(0.708)	(0.336)	(0.257)
Share of AI		-1.413*		-1.599**		-1.913**		-1.038***
		(0.751)		(0.655)		(0.818)		(0.297)
Share of Pricing		0.101		0.322		0.133		-0.035
		(0.196)		(0.253)		(0.213)		(0.077)
Log Sales		-0.106***		-0.123***		-0.136***		0.008**
		(0.009)		(0.008)		(0.010)		(0.003)
Log TFP		0.036*		0.165***		0.094***		-0.096***
		(0.020)		(0.018)		(0.021)		(0.008)
R&D/Sales		1.447***		1.090***		0.873***		0.274***
		(0.181)		(0.167)		(0.197)		(0.072)
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	0.068	0.148	0.093	0.191	0.054	0.125	0.019	0.062

Notes: Standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01. Industry fixed effects are controlled at the two-digit NAICS level. We run the following regression: $\Delta y_{j,[t1,t2]} = \beta \Delta APS_{j,[t1,t2]} + \gamma\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\} + \Gamma Z_{j,t1} + \gamma_s + \epsilon_j$, 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. And $\{\Delta AIS_{j,[t1,t2]}, \Delta PS_{j,[t1,t2]}\}$ measures the changes in AI share and Pricing share in the same fashion. Both the changes in AI share and Pricing share are orthogonal to $\Delta APS_{j,[t1,t2]}$, so AI pricing jobs are not picked up in either of the measures. We omit 2024Q1 for potential seasonality. $Z_{j,t1}$ 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.

D Supplements to Monetary Shock Analysis

D.1 Monetary Shocks: Using the Firm-level Adoption Dummy

In the main text, we measure firm-level AI pricing adoptions by the cumulative share of AI pricing jobs in all pricing jobs, which is a measure of AI pricing intensity. Here, we consider an alternative regression where we measure AI pricing adoptions using the adoption dummy ($\mathbb{1}^{AP}_{j,t-1}$), which is the cumulative incidence of AI pricing job postings until quarter $t-1$ for firm j, that is if firm j has ever posted one AI pricing job from the beginning of our sample until quarter $t-1$, $\mathbb{1}^{AP}_{j,t-1} = 1$.

In particular, we estimate the following empirical specification

$$\begin{aligned} R_{j,e} =& \beta_0 + \beta_1 MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{0} + \beta_2 MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{1} \\ &+ \beta_3 Z_{j,t-1} + \beta_4 FPA_s + \beta_5 MP_e \times FPA_s + \gamma_j + \epsilon_{je}. \end{aligned} \tag{D.1}$$

Table D1 presents the result of our regression specification (4) using the lagged AI-pricing dummy as an indicator of AI pricing adoption, where $Z_{j,t-1}$ includes the industry-level frequency of price adjustment FPA_s. Different columns vary in specifications by turning firm-level controls and firm fixed effects on and off. We do not include event fixed effects here, so we can see the average effects of monetary policy surprises. First, all columns show that monetary expansions cause positive stock returns at the firm level. The point estimate is economically large and statistically significant at the 1% level: a hypothetical policy surprise of 25 bps leads to an increase in a return of about 2.5 to 3.0 percentage points for firms that non-adopters of AI pricing ($\mathbb{1}^{AP}_{j,t-1} = \mathbf{0}$). Second, for firms that have ever adopted AI pricing up to period $t-1$ ($\mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$), the effects of the same policy surprise increase to about 2.7 to 3.2 percentage points. The gap between the two is about 0.3 percentage points and is quite robust and significant across different specifications. Third, the gap between the two is quantitatively comparable to the marginal effects of a higher frequency of price adjustment, with the magnitude of one standard deviation.

Table D1: Stock Return Response to Monetary Shocks: AI Pricing Dummy

	(1)	(2)	(3)	(4)	(5)	(6)
$MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{0}$	2.478***	2.487***	2.415***	2.933***	2.950***	2.910***
	(0.080)	(0.080)	(0.081)	(0.192)	(0.173)	(0.175)
$MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$	2.725***	3.021***	3.000***	2.953***	3.114***	3.182***
	(0.092)	(0.106)	(0.109)	(0.207)	(0.240)	(0.245)
$\mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$	0.023	-0.003	-0.074***	0.024	0.008	-0.046
	(0.014)	(0.017)	(0.026)	(0.033)	(0.037)	(0.060)
$MP_e \times FPA_s$				0.380***	0.385***	0.370***
				(0.140)	(0.129)	(0.129)
FPA_s				0.033**	0.018	
				(0.016)	(0.016)	
Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y
N	180236	145094	145094	48196	35890	35890
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 $\mathbb{1}^{AP}_{j,t-1}$ is a dummy indicator of the cumulative incidence of firm-level AI pricing adoption, lagged by one quarter. The key independent variable is the interaction between the AI pricing dummy and the monetary policy shock. 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.

D.2 Monetary Shocks: Additional Main Specification Results

D.2.1 Interactions with Firm-level Controls

Table D2: Stock Return Response to Monetary Shocks: Interaction with Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$MP_e \times APS_{j,t-1}$	6.739**	7.172***	6.458**	6.403**	6.705***	6.538**	6.455**	6.723***	6.487**	7.049***
	(2.702)	(2.694)	(2.598)	(2.597)	(2.597)	(2.597)	(2.596)	(2.602)	(2.596)	(2.714)
$MP_e \times FPA_s$	0.397***	0.384***	0.387***	0.379***	0.351***	0.362***	0.360***	0.357***	0.344***	0.332**
	(0.119)	(0.119)	(0.124)	(0.118)	(0.119)	(0.120)	(0.120)	(0.120)	(0.122)	(0.130)
MP_e × Share of AI	11.144**									13.078***
	(4.971)									(5.073)
MP_e × Share of Pricing		-1.918								-1.819
		(2.130)								(2.137)
MP_e × Log Sales			-0.006							0.045
			(0.084)							(0.108)
MP_e × Log Age				-0.167						-0.243
				(0.173)						(0.188)
MP_e × Log TFP					-0.415***					-0.579**
					(0.155)					(0.237)
MP_e × R&D/Sales						-1.166				-0.937
						(0.908)				(1.254)
MP_e × Log Tobin's Q							-0.345			-0.092
							(0.255)			(0.319)
MP_e × Cash/Asset								-1.192		-0.456
								(0.776)		(1.121)
MP_e × Log Markup									-0.338	0.371
									(0.239)	(0.375)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	23774	23774	24556	24556	24556	24556	24556	24556	24556	23774

*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 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.

D.2.2 Excluding Finance, IT, and Business Services

Table D3: Stock Return Response to Monetary Shocks: Interaction with Controls

	Excluding Finance, IT, and Business Services									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$MP_e \times APS_{j,t-1}$	6.759**	7.186***	6.475**	6.415**	6.725***	6.554**	6.468**	6.740***	6.505**	7.065***
	(2.700)	(2.693)	(2.596)	(2.595)	(2.596)	(2.595)	(2.595)	(2.600)	(2.595)	(2.712)
$MP_e \times FPA_s$	0.394***	0.381***	0.383***	0.376***	0.348***	0.357***	0.356***	0.353***	0.340***	0.325**
	(0.119)	(0.119)	(0.124)	(0.119)	(0.119)	(0.120)	(0.120)	(0.120)	(0.122)	(0.130)
MP_e × Share of AI	11.033**									12.969**
	(4.969)									(5.071)
MP_e × Share of Pricing		-1.906								-1.805
		(2.129)								(2.136)
MP_e × Log Sales			-0.004							0.046
			(0.084)							(0.108)
MP_e × Log Age				-0.180						-0.265
				(0.174)						(0.190)
MP_e × Log TFP					-0.411***					-0.568**
					(0.155)					(0.238)
MP_e × R&D/Sales						-1.203				-0.979
						(0.910)				(1.254)
MP_e × Log Tobin's Q							-0.350			-0.094
							(0.256)			(0.320)
MP_e × Cash/Asset								-1.209		-0.457
								(0.779)		(1.122)
MP_e × Log Markup									-0.344	0.355
									(0.239)	(0.375)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	23588	23588	24362	24362	24362	24362	24362	24362	24362	23588

*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 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.

D.3 Monetary Shocks: Additional Results of Asymmetric Effects

Table D4: Stock Return Response to Monetary Shocks: AI Pricing Dummy

Allowing for Asymmetric Effects of Monetary Shocks (MP_e^+ Stands for Easing)						
	(1)	(2)	(3)	(4)	(5)	(6)
$MP_e^+ \times \mathbb{1}_{j,t-1}^{AP} = \mathbf{0}$	3.430***	3.350***	3.365***	3.429***	3.423***	3.414***
	(0.172)	(0.170)	(0.171)	(0.412)	(0.372)	(0.373)
$MP_e^+ \times \mathbb{1}_{j,t-1}^{AP} = \mathbf{1}$	3.580***	3.123***	3.041***	3.163***	2.541***	2.345***
	(0.210)	(0.234)	(0.237)	(0.470)	(0.528)	(0.536)
$MP_e^- \times \mathbb{1}_{j,t-1}^{AP} = \mathbf{0}$	-1.836***	-1.905***	-1.762***	-2.598***	-2.631***	-2.567***
	(0.130)	(0.129)	(0.131)	(0.308)	(0.279)	(0.284)
$MP_e^- \times \mathbb{1}_{j,t-1}^{AP} = \mathbf{1}$	-2.230***	-2.958***	-2.968***	-2.826***	-3.460***	-3.701***
	(0.143)	(0.167)	(0.173)	(0.322)	(0.375)	(0.388)
$MP_e^+ \times FPA_s$				0.531*	0.407	0.424
				(0.299)	(0.275)	(0.275)
$MP_e^- \times FPA_s$				-0.271	-0.362*	-0.327
				(0.221)	(0.203)	(0.204)
Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y
N	180236	145094	145094	48196	35890	35890
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.

Table D5: Stock Return Response to Monetary Shocks: Interaction with Controls

	Allowing for Asymmetric Effects of Monetary Shocks (MP_e^+ Stands for Easing)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MP_e^+ \times APS_{j,t-1}$	0.222	-0.702	-1.117	-0.976	-0.561	-1.309	-0.510	-1.075	1.466
	(5.636)	(5.599)	(5.571)	(5.570)	(5.569)	(5.568)	(5.580)	(5.566)	(5.681)
$MP_e^- \times APS_{j,t-1}$	-11.466***	-12.466***	-11.089***	-10.958***	-11.131***	-11.106***	-11.144***	-11.068***	-11.385***
	(4.285)	(4.223)	(3.980)	(3.978)	(3.980)	(3.978)	(3.987)	(3.978)	(4.299)
$MP_e^+ \times FPA_s$	0.461*	0.455*	0.468*	0.461*	0.361	0.393	0.397	0.324	0.349
	(0.251)	(0.251)	(0.261)	(0.250)	(0.252)	(0.252)	(0.252)	(0.257)	(0.274)
$MP_e^- \times FPA_s$	-0.345*	-0.331*	-0.324	-0.318*	-0.331*	-0.331*	-0.322*	-0.347*	-0.304
	(0.190)	(0.190)	(0.198)	(0.189)	(0.190)	(0.192)	(0.191)	(0.194)	(0.208)
$MP_e^+ \times$ Share of AI	15.505								19.534
	(12.257)								(12.521)
$MP_e^- \times$ Share of AI	-6.586								-7.054
	(8.194)								(8.377)
$MP_e^+ \times$ Share of Pricing		10.976**							11.241**
		(5.309)							(5.318)
$MP_e^- \times$ Share of Pricing		8.272***							8.256**
		(3.200)							(3.212)
$MP_e^+ \times$ Log Sales			-0.036						0.014
			(0.181)						(0.230)
$MP_e^- \times$ Log Sales			-0.014						-0.077
			(0.134)						(0.174)
$MP_e^+ \times$ Log Age				0.216					0.192
				(0.361)					(0.389)
$MP_e^- \times$ Log Age				0.441					0.554*
				(0.283)					(0.307)
$MP_e^+ \times$ Log TFP					-0.855***				-0.789
					(0.325)				(0.493)
$MP_e^- \times$ Log TFP					0.106				0.343
					(0.253)				(0.386)
$MP_e^+ \times$ Log Tobin's Q						-0.970*			-0.150
						(0.556)			(0.691)
$MP_e^- \times$ Log Tobin's Q						-0.041			0.094
						(0.408)			(0.511)
$MP_e^+ \times$ Cash/Asset							-2.425		-0.718
							(1.678)		(2.186)
$MP_e^- \times$ Cash/Asset							0.396		0.876
							(1.232)		(1.655)
$MP_e^+ \times$ Log Markup								-1.092**	-0.147
								(0.524)	(0.780)
$MP_e^- \times$ Log Markup								-0.136	-0.509
								(0.381)	(0.567)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	23774	23774	24556	24556	24556	24556	24556	24556	23774

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

D.4 Monetary Shocks: Raw Shocks in Bauer and Swanson (2023)

Table D6: Stock Return Response to Raw Monetary Shocks: AI Pricing Dummy

	(1)	(2)	(3)	(4)	(5)	(6)
$MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{0}$	2.426***	2.408***	2.458***	2.868***	2.915***	2.972***
	(0.083)	(0.082)	(0.082)	(0.196)	(0.179)	(0.179)
$MP_e \times \mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$	3.033***	3.054***	3.172***	3.408***	3.240***	3.395***
	(0.098)	(0.112)	(0.114)	(0.218)	(0.253)	(0.257)
$\mathbb{1}^{AP}_{j,t-1} = \mathbf{1}$	0.037***	0.020	-0.055**	0.031	0.025	-0.039
	(0.014)	(0.017)	(0.026)	(0.033)	(0.038)	(0.060)
$MP_e \times FPA_s$				0.455***	0.471***	0.472***
				(0.146)	(0.133)	(0.133)
FPA_s				0.036**	0.017	
				(0.016)	(0.016)	
Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y
N	180236	145094	145094	48196	35890	35890

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 $\mathbb{1}^{AP}_{j,t-1}$ is a dummy indicator of the cumulative incidence of firm-level AI pricing adoption, lagged by one quarter. The key independent variable is the interaction between the AI pricing dummy and the monetary policy shock. 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 D7: Stock Return Response to Raw Monetary Shocks: Interaction with Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$MP_e \times APS_{j,t-1}$	6.150**	6.787**	6.744**	6.767**	7.243***	6.920**	6.825**	7.085**	6.874**	6.383**
	(2.843)	(2.825)	(2.772)	(2.771)	(2.771)	(2.771)	(2.770)	(2.776)	(2.770)	(2.854)
$MP_e \times FPA_s$	0.454***	0.440***	0.489***	0.439***	0.392***	0.418***	0.411***	0.419***	0.384***	0.404***
	(0.121)	(0.121)	(0.127)	(0.121)	(0.121)	(0.122)	(0.122)	(0.122)	(0.124)	(0.132)
MP_e × Share of AI	10.068**									12.610***
	(4.747)									(4.851)
MP_e × Share of Pricing		-2.385								-2.293
		(2.222)								(2.230)
MP_e × Log Sales			-0.101							-0.021
			(0.085)							(0.110)
MP_e × Log Age				-0.206						-0.225
				(0.174)						(0.189)
MP_e × Log TFP					-0.646***					-0.750***
					(0.158)					(0.240)
MP_e × R&D/Sales						-1.265				-1.415
						(0.890)				(1.230)
MP_e × Log Tobin's Q							-0.443*			-0.107
							(0.257)			(0.322)
MP_e × Cash/Asset								-1.076		-0.232
								(0.785)		(1.143)
MP_e × Log Markup									-0.500**	0.416
									(0.240)	(0.374)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	23774	23774	24556	24556	24556	24556	24556	24556	24556	23774

*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 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.

Table D8: Stock Return Response to Raw Monetary Shocks: Interaction with Controls

	Excluding Finance, IT, and Business Services									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$MP_e \times APS_{j,t-1}$	6.180**	6.805**	6.768**	6.783**	7.285***	6.945**	6.848**	7.107**	6.903**	6.423**
	(2.842)	(2.823)	(2.771)	(2.770)	(2.770)	(2.770)	(2.769)	(2.775)	(2.769)	(2.853)
$MP_e \times FPA_s$	0.450***	0.436***	0.486***	0.435***	0.389***	0.414***	0.407***	0.415***	0.381***	0.394***
	(0.121)	(0.121)	(0.127)	(0.121)	(0.122)	(0.122)	(0.123)	(0.122)	(0.124)	(0.132)
MP_e × Share of AI	9.921**									12.485**
	(4.745)									(4.851)
MP_e × Share of Pricing		-2.372								-2.276
		(2.221)								(2.230)
MP_e × Log Sales			-0.101							-0.017
			(0.085)							(0.111)
MP_e × Log Age				-0.239						-0.269
				(0.176)						(0.191)
MP_e × Log TFP					-0.646***					-0.748***
					(0.158)					(0.241)
MP_e × R&D/Sales						-1.292				-1.481
						(0.891)				(1.230)
MP_e × Log Tobin's Q							-0.447*			-0.107
							(0.259)			(0.323)
MP_e × Cash/Asset								-1.078		-0.236
								(0.787)		(1.144)
MP_e × Log Markup									-0.503**	0.412
									(0.240)	(0.374)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	23588	23588	24362	24362	24362	24362	24362	24362	24362	23588

*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 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.

E Supplements to the Model

E.1 Stylized Model: Additional Proofs

E.1.1 Proof of Lemma 1

Proof. The conditional maximization problem (8) implies the first order condition for each j:

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

which in terms of the linear demand function (7) is

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

Inverting to find p_j gives the solution. ∎

E.1.2 Proof of Lemma 2

Proof. The linear demand function (7) implies that for each individual j, the expected profit is

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

and Lemma 1 implies

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

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

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

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

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

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

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

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

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

E.1.3 Proof of Lemma 3

Proof. If firms prefer to adopt AI pricing (condition (17)), all of its first order conditions hold.

First we find the implied AI pricing inputs. $R'(N) = \frac{\rho}{\nu}$, so the first order condition (11) becomes

$$w = \mu\Phi\rho\beta L_b^{\beta-1}$$
$$\implies L_b = \left(\frac{\mu\Phi\rho\beta}{w}\right)^{\frac{1}{1-\beta}} \tag{E.2}$$

where $\Phi = \frac{(\bar{z}-\eta\kappa)^2}{4\eta}$. Equation (15) becomes

$$\frac{w}{q} = \frac{F_a(L_a, L_b, C)}{F_c(L_a, L_b, C)} = \frac{\alpha A^\alpha L_a^{\alpha-1}C^\gamma}{\gamma A^\alpha L_a^\alpha C^{\gamma-1}}$$
$$\implies \frac{C}{L_a} = \frac{w}{q}\frac{\gamma}{\alpha} \tag{E.3}$$

and equation (14) becomes

$$F_a(L_a, L_b, C) = F_b(L_a, L_b, C)$$
$$\alpha A^\alpha L_a^{\alpha-1}C^\gamma = \beta L_b^{\beta-1} \tag{E.4}$$

Plugging in equations (E.2) and (E.3) gives

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

$$\implies L_a = \left(\alpha^{1-\gamma}w^{\gamma-1}A^\alpha(\frac{\gamma}{q})^\gamma\mu\Phi\rho\right)^{\frac{1}{1-(\alpha+\gamma)}} \tag{E.5}$$

Equation (E.3) says computing is given by $C = \frac{\gamma w}{\alpha q} L_a$, so the condition in equation (17) becomes:

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

Equation (E.16) gives the solution for L_a. Plug it into the condition in equation (17):

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

which simplifies to

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

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

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

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

E.1.4 Proof of Lemma 4

Proof. Equation E.16 gives the pricing labor input as

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

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

■

E.1.5 Proof of Lemma 5

Proof. The share $\frac{L_a}{L_a+L_b}$ is increasing in μ if and only if the ratio $\frac{L_a}{L_b}$ is increasing. Conditional on adopting AI pricing, the ratio $\frac{L_a}{L_b}$ is given from equations (E.2) and (E.16) by

$$\frac{L_a}{L_b} = \alpha^{\frac{1-\gamma}{1-(\alpha+\gamma)}} \gamma^{\frac{\gamma}{1-(\alpha+\gamma)}} A^{\frac{\alpha}{1-(\alpha+\gamma)}} q^{\frac{-\gamma}{1-(\alpha+\gamma)}} w^{\frac{1}{1-\beta} - \frac{1-\gamma}{1-(\alpha+\gamma)}} (\mu \Phi \rho)^{\frac{1}{1-(\alpha+\gamma)} - \frac{1}{1-\beta}} \tag{E.6}$$

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

E.1.6 Proof of Lemma 6

Proof. Using the first order condition (E.3), the production function for observing components (16) becomes

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

and the labor choices (E.2) and (E.16) imply

$$N = \left(\frac{\mu\Phi\rho\beta}{w}\right)^{\frac{\beta}{1-\beta}} + A^\alpha \left(\frac{w}{q}\frac{\gamma}{\alpha}\right)^\gamma \left(\alpha^{1-\gamma} w^{\gamma-1} A^\alpha (\frac{\gamma}{q})^\gamma \mu\Phi\rho\right)^{\frac{\alpha+\gamma}{1-(\alpha+\gamma)}} \tag{E.7}$$

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

E.1.7 Proof of Lemma 7

Proof. The firm's revenue y is given by

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

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

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

which we can rewrite using unconditional expectations:

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

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

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

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

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

E.1.8 Proof of Lemma 8

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

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

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

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

which we can rewrite using unconditional expectations:

$$= \frac{y}{\kappa\mu\mathbb{E}\left[z_j - \frac{\mathbb{E}\left[z_j|\Omega\right]}{2} - \frac{\eta\kappa}{2}\right]} - 1 = \frac{y}{\kappa\mu\left(\frac{\bar{z}}{2} - \frac{\eta\kappa}{2}\right)} - 1 \tag{E.8}$$

Then substitute for revenue with equation (18):

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

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

E.1.9 Proof of Lemma 9

Proof. *Result (1)*: The definition (10) implies Φ is increasing in $\bar{z}$ because we assumed $\bar{z} > \eta\kappa$ so that firms make positive profits. L_b is increasing in Φ by equation (E.2), L_a is increasing in Φ by equation (E.16), and C is increasing in L_a by equation (E.3).

Result (2): The labor ratio $\frac{L_a}{L_b}$ is increasing in Φ if and only if $\beta < \alpha + \gamma$ by equation (E.6), and the share $\frac{L_a}{L_a+L_b}$ is increasing in the ratio $\frac{L_a}{L_b}$.

Result (3): Factor observation N is increasing $\bar{z}$ by *Result (1)*. Per equation (18), revenue y is increasing in both N and $\bar{z}$.

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

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

which simplifies by equations (18) and (E.8):

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

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

■

E.1.10 Proof of Proposition 5

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

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

where the function $N(\bar{z}, \mu)$ is given by equation (E.7).

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

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

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

$$\frac{\partial^2 \pi(\bar{z}, \mu)}{\partial \mu \partial \bar{z}} = \frac{\rho}{2\eta}\frac{\partial N(\bar{z}, \mu)}{\partial \bar{z}} + \frac{\mu\rho}{2\eta}\frac{\partial^2 N(\bar{z}, \mu)}{\partial \mu \partial \bar{z}} + \frac{\bar{z} - \eta\kappa}{\eta} \tag{E.9}$$

The partial derivatives are

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

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

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

and

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

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

By assumption $\bar{z} > \eta\kappa$, so per the definition (10) $\frac{\partial\Phi}{\partial\bar{z}} > 0$. Thus, all terms in equation (E.9) are positive. ■

E.2 Stylized Model: Time-Series and Cross-Section Data

Table F1: Time Series of AI pricing adoption

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

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

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

We first deflate the release prices by the Consumer Price Index, with the 2023 price normalized to 1 dollar. We then choose the single precision giga (1 billion) floating-point operations per second (GFLOPs) as our measure of performance. We then calculate the inflation-adjusted dollar per performance, dividing the former by the latter. We average the dollar per performance if there are multiple releases within a year, and we linearly interpolate the dollar per performance if there are no releases for a specific year. Table F1 column 5 shows this data series.

Table F2: Cross Section of AI Pricing in 2023

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

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

Cross Section of the Size Adoption Correlations Our cross-section data for the size adoption correlations are taken from our Lightcast Compustat merged dataset for the year 2023. We sort the firm-quarter observations in sales and group them into twenty bins of an equal number of firm-quarter observations. Table F2 summarizes this data.

E.3 Extension: Labor Wage Differential

This section extends the baseline model of Section 6 to allow the two types of pricing labor to have different wages and then explores the consequences.

The firm faces the same pricing problem as in the baseline model, but now, each type of pricing labor is paid a distinct wage. As before, basic pricing labor L_b charges wage w, but AI pricing labor L_a charges wage θw, where $\theta > 1$ captures the wage premium for AI workers. Computing still costs q.

With these modifications, the firm's problem becomes

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

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

where $\mathbb{1}(L_a C > 0)$ is an indicator function that takes value 1 if and only if both AI pricing inputs L_a and C are strictly positive. The first order conditions for basic pricing labor (11) and computing (13) are unchanged, but the first order condition for AI pricing labor (conditional on adoption) is now

$$\mu\Phi\nu R'(N) F_a(L_a, L_b, C) = \theta w \tag{E.10}$$

Therefore, the marginal products of the two labor types are related by

$$F_a(L_a, L_b, C) = \theta F_b(L_a, L_b, C) \tag{E.11}$$

and the marginal rate of transformation between AI pricing labor and computing becomes:

$$\frac{F_a(L_a, L_b, C)}{F_c(L_a, L_b, C)} = \frac{\theta w}{q} \tag{E.12}$$

These first-order conditions only apply if the firms adopt non-zero AI pricing. They only do so if the value of the output from the AI technology $(AL_a)^\alpha C^\gamma$ is at least as large as the associated costs. The new adoption condition is

$$\mu\Phi(AL_a)^\alpha C^\gamma \geq \theta w L_a + qC + \chi \tag{E.13}$$

If AI pricing commands a wage premium in the labor market ($\theta > 1$), this affects firms' AI adoption along both the extensive and intensive margins. AI pricing labor is more expensive, so firms will be less willing to use the technology at all, and if they do, they will hire less AI pricing labor. Proposition E.1 formalizes this result.

Proposition E.1 *If $\alpha + \gamma < 1$ and $\theta > 0$ is the AI pricing wage premium, then:*

1. *The AI share of pricing labor $\frac{L_a}{L_a+L_b}$ is decreasing in θ.*
2. *The minimum market size μ such that firms are willing to use AI pricing is increasing in θ.*

Proof. If firms prefer to adopt AI pricing (condition (E.13)), all of its first order conditions hold. Basic pricing labor demand is unchanged from the baseline model, given by $L_b = \left(\frac{\mu\Phi\rho\beta}{w}\right)^{\frac{1}{1-\beta}}$.

With the wage differential, equation (E.12) becomes

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

$$\implies \frac{C}{L_a} = \frac{\theta w}{q}\frac{\gamma}{\alpha} \tag{E.14}$$

and equation (E.11) becomes

$$\alpha A^\alpha L_a^{\alpha-1} C^\gamma = \theta\beta L_b^{\beta-1} \tag{E.15}$$

Plugging in equations (E.2) and (E.14) gives

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

$$\implies L_a = \left(\alpha^{1-\gamma}(\theta w)^{\gamma-1} A^\alpha (\frac{\gamma}{q})^\gamma \mu\Phi\rho\right)^{\frac{1}{1-(\alpha+\gamma)}} \tag{E.16}$$

The assumption that $\alpha + \gamma < 1$ ensures that L_a is decreasing in θ. L_b is unaffected by θ, so the AI pricing share must also be decreasing in θ, proving the first statement.

Equation (E.14) says computing is given by $C = \frac{\gamma\theta w}{\alpha q} L_a$, so the condition in equation (E.13) becomes:

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

Equation (E.16) gives the solution for L_a. Plugging it in:

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

which simplifies to

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

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

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

The assumption that $1>(\alpha+\gamma)$ ensures that this function is increasing in q and increasing in θ. This proves the second statement. ■

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