The Rise of AI Pricing:

Trends, Driving Forces, and Implications for Firm Performance

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Hong Kong University of Science and Technology (Guangzhou)

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Motivation

- Recent rise of AI has spurred interest in studying the macro effects of new technologies
  - Labor market, economic growth, income inequality, firm performance, market concentration, ...

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- I/O and business literature have studied how AI pricing affects firm pricing decisions and market competitiveness, focusing on specific industries
  - Online retailing (Wang et al., 2023), housing rental (Calder-Wang and Kim, 2023), gasoline (Clark et al., 2023), and online pharmaceuticals (Brown and MacKay, 2023)

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- There is no economy-wide (macro) analysis of AI pricing

AI pricing vs traditional pricing

- AI pricing differs from traditional pricing in three key ways:
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- Expectations of today: Just a starting point! (投石问路)

This paper

- Document stylized facts on AI pricing
  - Aggregate adoption trends over time and variations across industries
  - Firm-level driving forces of adoption
  - Correlations with firm performance

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  - Correlations with firm performance
- Examine how AI pricing affects the sensitivity of firm stock returns to high-frequency monetary policy shocks, indicating the potential role of price discrimination
- Present a simple model to rationalize stylized facts and monetary shock effects
  - Model features a monopolist facing imperfect information about its demand function and investing in both traditional and AI-powered pricing to acquire information
  - Model mechanism: AI pricing enhances price discrimination
  - Model predictions in line with stylized facts

Data and measure

- We use Lightcast job posting data (2010-2024Q1) to identify AI pricing job posts
  - Identify jobs requiring AI skills using the ▸ narrow AI skill categories (Acemoglu et al., 2022)
  - Search for the keyword “pricing" in the job title, skill requirements, and job description
  - AI-pricing job requires AI-related skills *and* contains the keyword “pricing"

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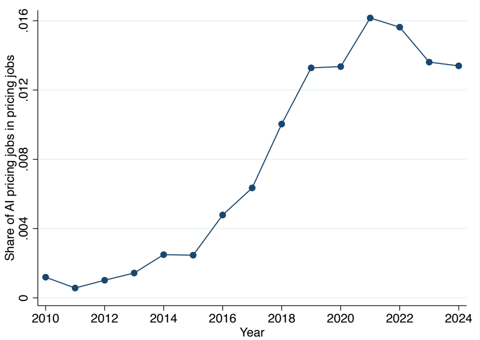
- Aggregate AI-pricing job posts to firm level and merge with Compustat to study firm-level determinants of adoptions and correlations with firm performance
- Merge data with CRSP daily stock returns to study how AI pricing affects responses of stock returns to monetary policy shocks

[The Rise of AI Pricing]

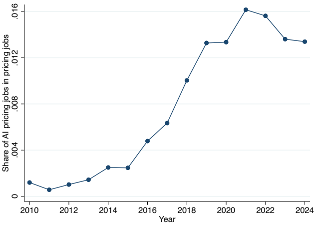
Aggregate trends of AI pricing jobs



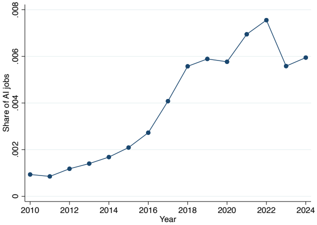
- Share of AI pricing jobs in all pricing jobs surged over 10 times (from 0.12% in 2010 to 1.34% in 2024), with most increases after 2015

Aggregate trends of AI pricing, AI jobs, and pricing jobs

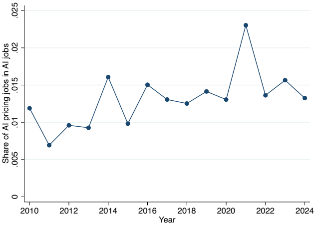
▸ Robustness



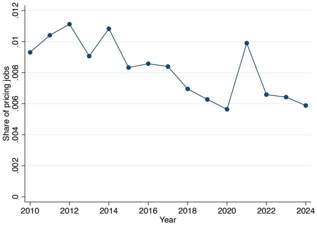
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Jobs in All Jobs



(c) Share of AI Pricing in AI Jobs



(d) Share of Pricing Jobs in All Jobs

Evolution of AI pricing job posts: The case of Uber

- Uber is an interesting company to provide news releases about each step of the adoption
- This helps us to roughly externally validate our measure
  - 2011: www.uber.com/newsroom/take-a-walk-through-surge-pricing/
  - 2013: www.uber.com/en-GB/newsroom/nye-2012-surge
  - 2017: www.uber.com/en-ZA/blog/scaling-michelangelo/
  - 2019: www.uber.com/blog/uber-ai-blog-2019/
- Similar cases of Amazon and JP Morgan Chase Other Cases

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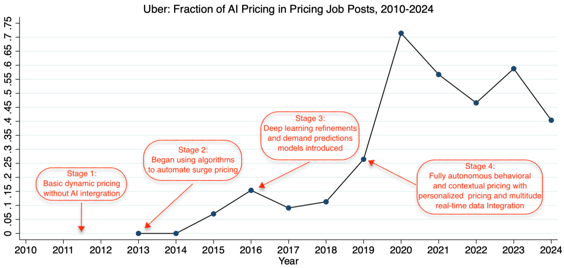
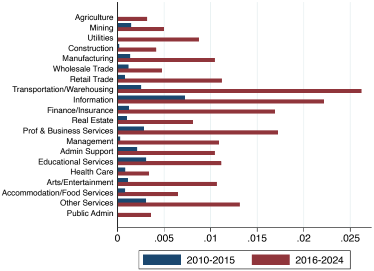


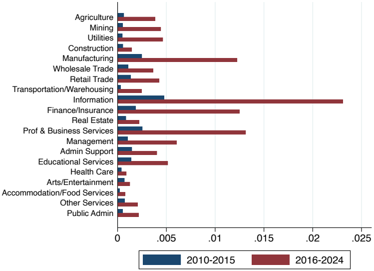
Leading firms in AI pricing job postings

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%

Variations across industries: AI pricing vs. general AI



(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Jobs in All Jobs

- Rapid rise of AI pricing after 2015 spread to broader set of industries than general AI

Takeaways

- AI pricing adoption has been rising rapidly:
  - Share of AI pricing jobs in all pricing jobs has surged by more than 10-fold, with the sharpest increases after 2015
  - During the same period, pricing jobs in all jobs declined by about 40% (from 0.93% to 0.59%)

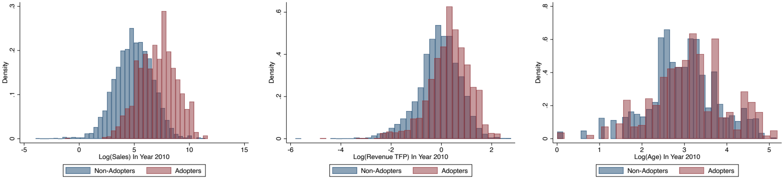
Takeaways

- AI pricing adoption has been rising rapidly:
    - Share of AI pricing jobs in all pricing jobs has surged by more than 10-fold, with the sharpest increases after 2015
    - During the same period, pricing jobs in all jobs declined by about 40% (from 0.93% to 0.59%)
- Adoptions of AI pricing have been widespread across industries
    - Growth in general AI jobs concentrated in IT, business services, finance, and manufacturing
    - In contrast, growth in AI pricing jobs is observed in a broader set of industries

[Firm-level Determinants of Adoption]

Distributions of adopters and non-adopters

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



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

- Adopters are firms that have posted at least one AI pricing job by 2024Q1
- Non-adopters are those who have never posted AI pricing jobs

Firm-level Determinants of Adoption

[Skipping details for time constraints, basic takeaways are below]

- Large, productive, and R&D intensive firms are more likely to adopt and adopt more
- Other factors such as firm age, financial conditions (leverage, liquidity, cash flows), and operational conditions (Tobin's Q, ROA, markup) are not consistently important
- Detailed regressions are here: ▸ Firm-level Determinants of Adoption

[AI Pricing and Firm Performance]

AI pricing and firm growth: Long-diff regressions

	Δ Log Sales		Δ Log Employment		Δ Log Assets		Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.193***	1.137***	0.996***	0.875***	1.134***	1.197***	0.259	0.259**
	(0.332)	(0.305)	(0.286)	(0.268)	(0.343)	(0.332)	(0.166)	(0.121)
Share of AI		-0.371		-0.637		-0.702		-0.628**
		(0.698)		(0.609)		(0.760)		(0.276)
Share of Pricing		0.068		0.231		0.080		-0.050
		(0.190)		(0.236)		(0.207)		(0.075)
Log Sales		-0.103***		-0.121***		-0.133***		0.009***
		(0.009)		(0.008)		(0.010)		(0.003)
Log TFP		0.046**		0.175***		0.106***		-0.092***
		(0.019)		(0.018)		(0.021)		(0.008)
R&D/Sales		1.559***		1.202***		1.002***		0.318***
		(0.179)		(0.165)		(0.195)		(0.071)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4014	3777	3677	3471	4025	3781	4014	3777
adj. R^2	0.064	0.145	0.086	0.188	0.049	0.121	0.018	0.059

- AI pricing adoptions are correlated with higher firm growth and higher markup
- Results are robust after controlling for changes in AI jobs and pricing jobs

AI pricing and firm growth: By firm size

Table1: AI Pricing and Heterogeneous Firm Performance: Long-differences

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

- Correlations of AI pricing with firm growth are stronger for larger firms

Evidence from high-frequency monetary shocks

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

- $R_{j,e}$: daily stock return of firm j on the event date e (percent, CRSP)
- MP_e: monetary policy surprises on event date e from Bauer and Swanson (2023) (sign-flipped, normalized to 25 bps changes)
- $APS_{j,t-1}$: AI pricing share of firm j in quarter $t-1$ [also consider AI pricing adoption dummy $\mathbb{1}^{AP}_{j,t-1}$ in the paper]
- $Z_{j,t-1}$: lagged firm-level controls (sales, TFP, Tobin's Q, cash/asset, markup, lags of AI job share or pricing job share
- Also consider frequency of price adjustments FPA_s in NAICS 6-digit industry s as in Pasten, Schoenle, and Weber (2020) and its interaction with MP_e

Stock return response to monetary shocks

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

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

- From non-adopter ($APS = 0$) to Amazon ($APS = 15\%$), 25 bps policy easing raises stock returns by extra 1 pp
- Effects similar to raising FPA by 2.5 standard deviations

Downstream versus upstream firms

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

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

- Use the industry-level measure of upstreamness from Antràs et al. (2012)
- Amplification effects concentrated in downstream firms, which are closer to consumers

Asymmetric effects of monetary shocks

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

MP_e^+ stands for policy easing, MP_e^- for tightening. Robust standard errors are in parentheses. * p<.1, ** p<0.05, *** p<0.01.

- Amplification effects of AI pricing are stronger for policy tightening than for easing

Robustness of long differences/monetary shocks

We examine the robustness of the long-differences results:

- Excluding finance and utility firms
- Excluding IT firms
- Excluding business and professional services firms
- Excluding all the above firms
- Excluding largest firms in top 1%, 5%, or 10%
- Controlling for changes in AI share and pricing share

We examine the robustness of the monetary shocks results:

- Excluding all the above firms
- Interaction of monetary shocks with all controls
- Using non-orthogonalized monetary shocks

Takeaways

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  - Amplification effects are asymmetric: stronger for policy tightening than for easing
  - Consistent with the asset pricing literature that "high markup firms are particularly risky at the downside" (Corhay, Li, and Tong, 2022; Corhay et al., 2023)

[A Stylized Theoretical Model]

Model environment

- A monopolist produces a single good at marginal cost κ and sells to a continuum of customers with measure μ

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- Firm sets p_j conditional on its information set Ω to maximize expected profit

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

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- Optimal pricing with uncertain demand:

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

Information structure

- Demand shifter z_j is a function of observable factors (data) x_j

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

where $\mathbb{E}[z_j] = \bar{z}$ is a known, but $\{b(n)\}_{n=0}^{\infty}$ are ex ante unknown

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- Firm can observe up to N factors (ordered in declining importance) such that

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- Signal-noise ratio increases with N

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

where $\nu \equiv \mathbb{V}\left[z_j\right]$ and $R'(N) > 0$

Information acquisition and optimal pricing

- Expected profit conditional on demand signals $R(N)$

$$\mathbb{E}\left[\int_{j\in\mathcal{J}} \pi_j(p_j)dj\right] = \mu\Phi\nu R(N), \quad \Phi \equiv \frac{(\overline{z}-\eta\kappa)^2}{4\eta}$$

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- AI pricing incurs fixed cost $\chi \rightarrow$ discrete adoption of AI pricing
- Optimal information acquisition decisions

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

$$s.t. \quad N = L_b^{\beta} + (AL_a)^{\alpha} C^{\gamma}$$

Model predictions

1. Adoption of AI pricing increases as computing price q falls (Prop 1)
2. Share of AI labor $\frac{L_a}{L_a+L_b}$ increases as q falls (Prop 2)
3. Given q, the share of AI labor increases with firm size (revenue) (Prop 3)
4. Given q, the share of AI labor increases with firm markup (Prop 4)
5. Gross profit π more sensitive to demand shift $\bar{z}$ for firms with more AI pricing

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*Now, we want to see if this super simple model could roughly match our stylized facts

Data to match: Aggregate trends

Table2: 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

*The data source for the AI Pricing is our Lightcast, and the data source for the AI computing cost is Epoch AI on the single precision giga (1 billion) floating-point operations per second (GFLOPs) per inflation-adjusted dollar of newly released GPUs of the year.

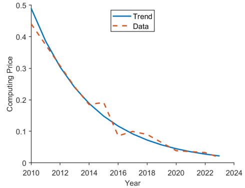
Data to match: Cross-section

Table3: Cross Section of AI Pricing in 2023

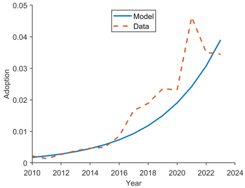
Size Group	Log Sales	AI pricing Share	Adoption Rate	Observations
1	0.8516183	0.00%	0.00%	382
2	2.759726	0.00%	0.00%	383
3	3.460735	0.00%	0.00%	383
4	3.975862	0.00%	0.00%	382
5	4.383954	0.00%	0.00%	383
6	4.735429	0.00%	0.00%	383
7	5.013049	0.00%	0.00%	382
8	5.263219	0.83%	0.26%	383
9	5.52475	0.58%	0.52%	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

Model predictions in line with empirical evidence

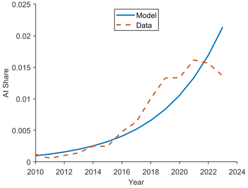
- Model simulated based on trends in GPU prices (q) with parameters $\beta = 0.75$, $\alpha = 0.6, \gamma = 0.2, A = 0.18, \Phi = 1, \rho = 1, \xi = 5, \mu_{min} = 0.15$.



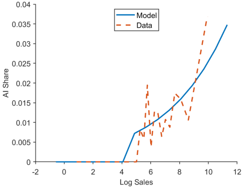
(a) AI Computing Cost



(b) Share of Firms Using AI Pricing



(b) AI Share of Pricing Labor



(d) AI Share of Pricing in Cross-Section

Concluding remarks

- AI pricing is rising rapidly and spreading broadly across industries

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- How about price stickiness? We need to find out about it

In-progress

- "AI Pricing and Price Stickiness: Evidence from BLS Micro-PPI Data"
  by Jonathan Adams, Min Fang, Yajie Wang, Zheng Liu
  **Trying to find out how the monthly price stickiness changes after AI pricing adoption of all industries in the U.S., using the Micro-PPI data from the Bureau of Labor Statistics*

- "Pricing Automation with Artificial Intelligence: Evidence from U.S. Retail Chains"
  by Zirou Chen, Carlos Estrada, Min Fang, Avi Goldfarb, Zheng Liu
  **Trying to find out how the weekly price stickiness and spatial discrimination change after AI pricing adoption of retailer chains in the U.S., using the retail data*

- "Monetary Policy in the Age of Pricing Automation"
  by Jonathan Adams, Min Fang, Yajie Wang, Zheng Liu
  **Trying to find out how the effectiveness of monetary policy changes considering both the changes in price stickiness and price discrimination in the data*

Appendix

AI skill categories of Acemoglu, Autor, Hazell, and Restrepo (2022)

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

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The rise of AI pricing: Aggregate trends

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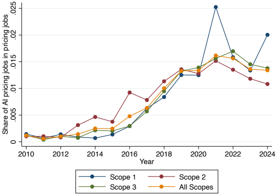
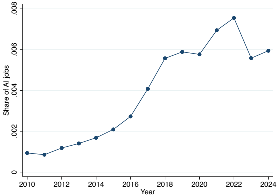
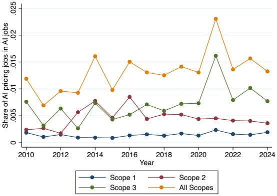
Figure1: Aggregate Time Trends of AI Pricing, Pricing, and AI Jobs (Other Scopes)



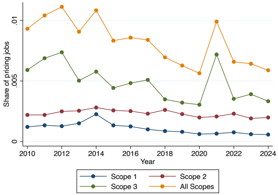
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Jobs in All Jobs



(c) Share of AI Pricing in AI Jobs



(d) Share of Pricing Jobs in All Jobs

The rise of AI pricing: The case of Amazon

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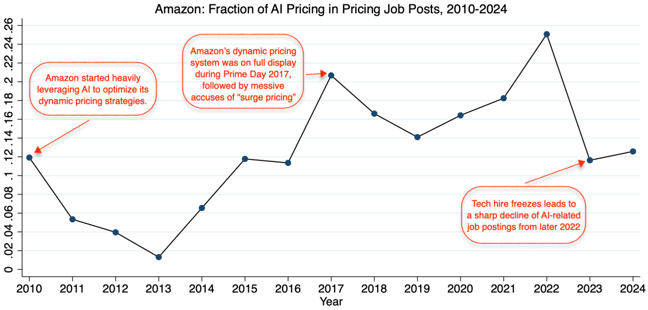
Figure2: Timeline of AI Share of Pricing Job Posts by Amazon



The rise of AI pricing: The case of JP Morgan Chase

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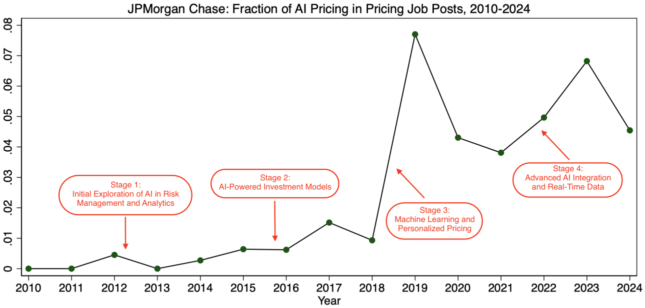
Figure3: Timeline of AI Share of Pricing Job Posts by JPMorgan Chase



Firm-level Determinants of Adoption

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Table4: Firm-level Determinants of AI Pricing Adoption

	AI Pricing Adopter Dummy Indicator, 2010-2024Q1 ($\mathbb{1}^{AP}_{j,2024Q1} = 1$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.089***									0.107***
	(0.002)									(0.003)
Log TFP 2010		0.103***								0.020***
		(0.006)								(0.007)
Log Age 2010			0.032***							-0.004
			(0.005)							(0.005)
Tobin's Q 2010				0.011***						0.011***
				(0.003)						(0.004)
Log Markup					0.016**					0.021*
					(0.007)					(0.012)
R&D/Sales 2010						-0.000				0.335***
						(0.000)				(0.057)
ROA 2010							-0.225***			0.122
							(0.081)			(0.098)
Cash/Assets 2010								-0.104***		0.004
								(0.023)		(0.033)
Debt/Assets 2010									0.071***	-0.053**
									(0.020)	(0.022)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	7797	7776	7787	7299	6342
adj. R^2	0.205	0.060	0.022	0.018	0.017	0.017	0.017	0.019	0.015	0.236

Firm-level Determinants of Adoption

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Table5: Firm-level Determinants of Cumulative AI Pricing Job Postings

	Total AI pricing job Postings, 2010-2024Q1 ($APN_{j,2024Q1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	3.754***									4.161***
	(0.210)									(0.233)
Log TFP 2010		5.485***								1.585***
		(0.547)								(0.585)
Log Age 2010			1.417***							0.446
			(0.502)							(0.413)
Tobin's Q 2010				1.126***						0.112
				(0.291)						(0.289)
Log Markup 2010					0.594					0.600
					(0.627)					(0.897)
R&D/Sales 2010						-0.006				10.122**
						(0.024)				(4.426)
ROA 2010							-8.341			6.158
							(7.489)			(7.642)
Cash/Assets 2010								1.962		5.283**
								(2.134)		(2.556)
Debt/Assets 2010									1.721	-2.635
									(1.388)	(1.677)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	7797	7776	7787	7299	6342
adj. R^2	0.053	0.028	0.016	0.016	0.014	0.014	0.014	0.014	0.007	0.078

Firm-level Determinants of Adoption

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Table6: Firm-level Determinants of AI Pricing Intensity

	Total AI Pricing Job Postings/Total Pricing Job Postings, 2010Q1-2024Q1 ($APS_{j,t}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.001***									0.001
	(0.000)									(0.000)
Log TFP 2010		0.004***								0.003**
		(0.001)								(0.001)
Log Age			-0.002***							-0.003***
			(0.001)							(0.001)
Tobin's Q 2010				0.001***						0.001
				(0.000)						(0.001)
Log Markup 2010					0.001					-0.002
					(0.001)					(0.002)
R&D/Sales 2010						-0.000				0.021**
						(0.000)				(0.009)
ROA 2010							0.008			-0.017
							(0.017)			(0.025)
Cash/Assets 2010								0.008**		-0.000
								(0.004)		(0.005)
Debt/Assets 2010									0.003	0.005
									(0.003)	(0.003)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	6229	5826	5925	6238	6215	6244	6232	6240	5875	5286
adj. R^2	0.010	0.012	0.012	0.011	0.009	0.009	0.009	0.010	0.010	0.015

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