The Rise of AI Pricing:

Trends, Driving Forces, and Implications for Firm Performance

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Information Systems and Operations Management

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Motivation

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

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  - Unlike traditional price-setting, AI pricing uses advanced algorithms for predictive analysis of large data, even incorporating real-time changes in market conditions
- I/O and business literature has studied how AI pricing affects firm pricing decisions and market competitiveness, focusing on very specific industries
  - online retailing (Aparicio, Eckles, and Kumar, 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 economic-wide (macro) analysis of AI pricing

This paper

- Document stylized facts on AI pricing
  - Aggregate adoption trends over time and variations across industries
  - Firm-level driving forces of adoption
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- Provide validations using externally identified monetary policy shocks
  - Examine implications of firm's AI pricing adoption for firm's stock return responses to externally identified high-frequency monetary policy shocks
- 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 predictions of stylized facts as the price of computing falls
  - Model predictions of demand shifters (monetary shocks) on firm performance

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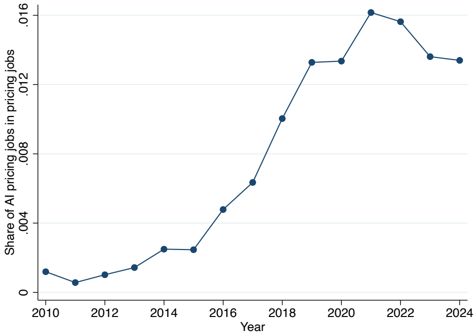
- Aggregate AI-pricing job posts to firm level and merge with Compustat to study firm-level determinants of adoptions and correlations with firm performance
- Merge data with CRSP daily stock returns to study how AI pricing affects responses of stock returns to monetary policy shocks

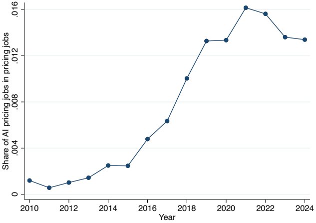
[The Rise of AI Pricing]

Aggregate time trends of AI pricing jobs

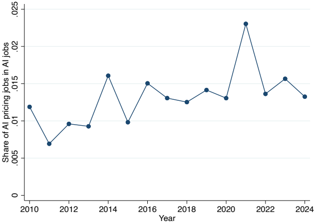


- The share of AI pricing job postings in all pricing job postings increased from 0.12% in 2010 to 1.56% in 2021 and then decreased with the tech bust in 2022.

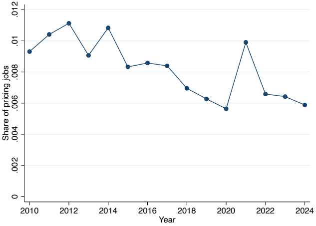
Aggregate time trends of AI pricing, pricing, and AI jobs



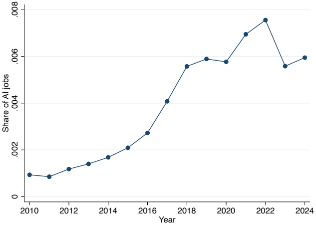
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Pricing in AI Jobs



(c) Share of Pricing Jobs in All Jobs



(d) Share of AI Jobs in All Jobs

Evolution of AI pricing job posts by 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/

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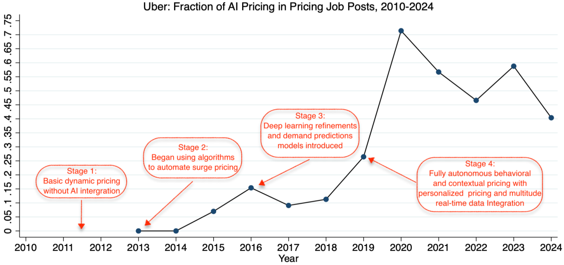
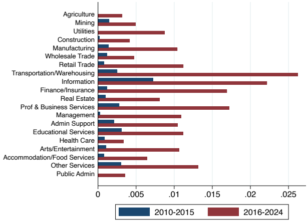


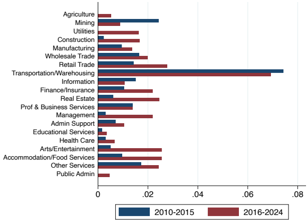
Leading firms in AI pricing job postings

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%

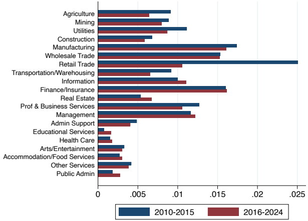
Variations across industries



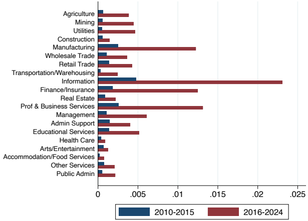
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Pricing in AI Jobs



(c) Share of Pricing Jobs in All Jobs



(d) Share of AI Jobs in All Jobs

Takeaways

- AI pricing adoption has been rising rapidly:
  - Share of AI pricing jobs in all pricing jobs has surged by more than 10 fold, from 0.12% in 2010 to 1.34% in 2024, with sharpest increases after 2016
  - During the same period, pricing jobs in all jobs declined by about 40% (from 0.93% to 0.59%)

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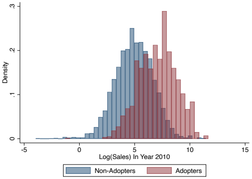
- AI pricing adoption has been rising rapidly:
    - Share of AI pricing jobs in all pricing jobs has surged by more than 10 fold, from 0.12% in 2010 to 1.34% in 2024, with sharpest increases after 2016
    - During the same period, pricing jobs in all jobs declined by about 40% (from 0.93% to 0.59%)
- 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 observed in a broader set of industries

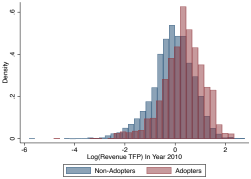
[Firm-level Determinants of Adoption]

Distributions of adopters and non-adopters

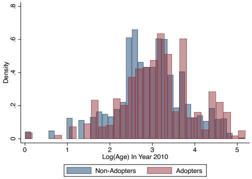
Figure1: Distributions of AI Pricing Adopters and Non-Adopters In the Year 2010



(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 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 AI pricing adoption

	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

Takeaways

- Large, productive, and R&D intensive firms are more likely to adopt and adopt more
- Age, financial conditions, and operation conditions do not matter much

[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***	1.134***	0.996***	0.871***	1.134***	1.197***	0.259	0.258**
	(0.332)	(0.305)	(0.286)	(0.268)	(0.343)	(0.332)	(0.166)	(0.121)
Share of AI		-0.374		-0.636		-0.696		-0.633**
		(0.698)		(0.608)		(0.760)		(0.276)
Share of Pricing		0.068		0.230		0.079		-0.050
		(0.190)		(0.236)		(0.207)		(0.075)
Log Sales		-0.103***		-0.119***		-0.132***		0.008**
		(0.009)		(0.008)		(0.009)		(0.003)
Log TFP		0.048**		0.176***		0.103***		-0.090***
		(0.019)		(0.018)		(0.021)		(0.008)
R&D/Sales		1.554***		1.198***		1.006***		0.316***
		(0.179)		(0.164)		(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	0.189	0.049	0.121	0.018	0.058

AI pricing and firm growth: By firm size

	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	0.401	0.606	0.401	0.606	0.401	0.116	-0.153
	(0.516)	(0.504)	(0.516)	(0.504)	(0.516)	(0.504)	(0.263)	(0.198)
$\Delta APS_{j,[2010,2023]} \times$ Size Medium	2.008***	1.745***	2.008***	1.745***	2.008***	1.745***	1.024***	1.187***
	(0.605)	(0.561)	(0.605)	(0.561)	(0.605)	(0.561)	(0.309)	(0.220)
$\Delta APS_{j,[2010,2023]} \times$ Size Large	2.919***	3.174***	2.919***	3.174***	2.919***	3.174***	-0.456	-0.200
	(0.875)	(0.822)	(0.875)	(0.822)	(0.875)	(0.822)	(0.446)	(0.323)
Controls	N	Y	N	Y	N	Y	N	Y
Industry $\times$ Szie Group FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4005	3777	4005	3777	4005	3777	4005	3777
adj. R^2	0.135	0.182	0.135	0.182	0.135	0.182	0.061	0.111

Evidence from high-frequency monetary shocks

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

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

Stock return response to monetary shocks: AI pricing dummy

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

Stock return response to monetary shocks: AI pricing share

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

Stock return response to monetary shocks: Interaction with controls

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

Takeaways

- AI pricing adoptions are associated with higher growth and higher markups
- AI pricing amplifies responses of stock returns to expansionary monetary policy shocks
  - Stock returns increase by 0.5 pp more for adopters over non-adopters following 25 bps easing
  - *An example of extrapolation:* From non-adopter ($APS = 0$) to Amazon ($APS = 16\%$), stock returns increase by 1 extra pp following 25 bps policy easing
- Going from From non-adopter ($APS = 0$) to Amazon ($APS = 16\%$), effects on stock return responses to MP are equivalent to raising FPA by about two standard deviation

[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
- Demand function of customer j

$$d_j(p_j) = z_j - \eta p_j$$

where firm has imperfect information about z_j

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

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

- 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

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

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

- 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

- Firm acquires information using basic pricing labor L_b or AI pricing labor L_a combined with computing equipment C

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

- AI pricing incurs fixed cost $\chi \rightarrow$ discrete adoption of AI pricing
- Expected profit

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

- Firm solves the optimizing problem

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

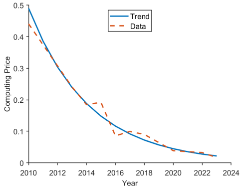
$$s.t.\ N = F(L_a, L_b, C)$$

Model predictions

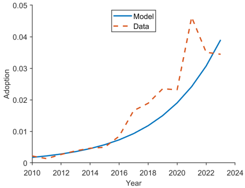
1. Adoption of AI pricing increases as computing price q falls (Prop 1)
2. Share of AI labor $\frac{L_a}{L_a+L_b}$ increases as q falls (Prop 2)
3. Given q, share of AI labor increases with firm size (revenue) (Prop 3)
4. Given q, the share of AI labor increases with firm markup (Prop 4)
5. Gross profit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

Model predictions in line with empirical evidence

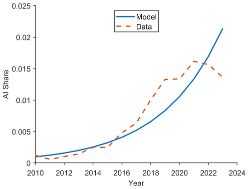
- Model simulated based on trends in GPU prices (q) with parameters $\beta = 0.75$, $\alpha = 0.6, \gamma = 0.2, A = 0.18, \Phi = 1, \rho = 1, \xi = 5, \mu_{min} = 0.15$.



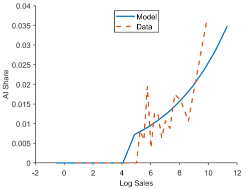
(a) AI Computing Cost



(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 spread broadly across industries
- Large and high-productivity firms are more likely to adopt AI pricing, and adoptions are associated with better firm performance
- Preliminary evidence suggests that AI pricing may act as reducing price stickiness and increasing markup (potentially also reflecting price discrimination) in the aggregate
- In-progress: Combine our measure with BLS product-level micro-PPI data to study causal evidence on how AI pricing adoption affects firms' pricing decisions

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.

Return to Data

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