



The Rise of Al Pricing: Trends, Driving Forces, and Implications for Firm Performance

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Motivation: General

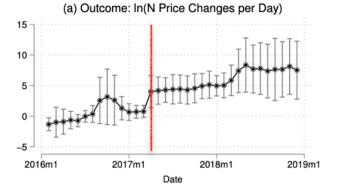
- Recent advances in artificial intelligence (AI) have spurred many studies aiming to understand the macroeconomic impact of the new technologies and the related policy implications.
 - Topics: labor market, economic growth, income inequality, firm growth, market concentration
 - A lesser-known area is the rise of AI-powered algorithmic pricing (or AI pricing hereafter).
- Unlike traditional price-setting technologies, AI pricing can
 - Incorporate a wide range of information for firms' pricing decisions
 - Respond to real-time changes in demand and supply conditions
- Recent studies have focused on the impact of AI pricing on market competitiveness or collusion outcomes in specific industries: online retailing, housing rental, gasoline, and pharmaceuticals
- How is the economic-wide adoption? And will there be aggregate implications?

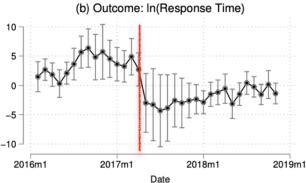
Motivation: An Example

Example from the German Gasoline Market: Assada-Clarkb-Ershovc-Xu'24 (JPE)

Figure 2: % Difference Between Adopters and Non-Adopters

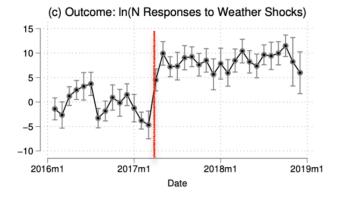
more frequent changes

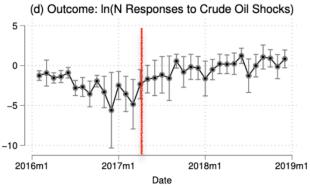




shorter response time to rival's price change

quicker response to shocks





quicker response to shocks

This Paper

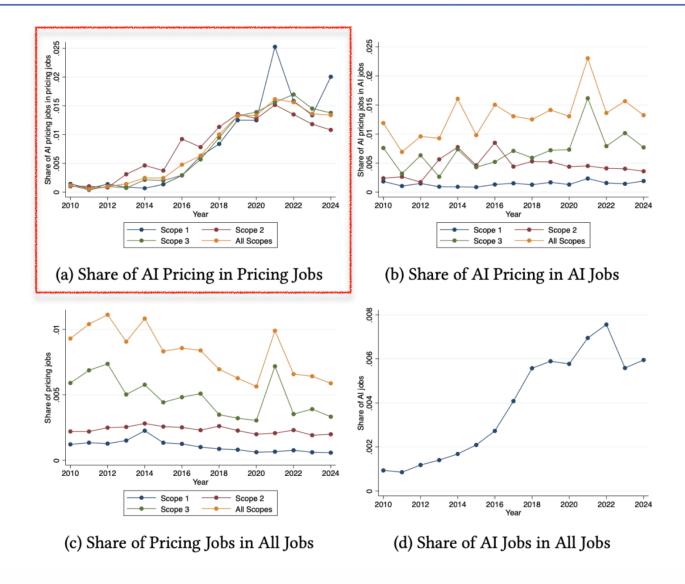
- Today: Document economic-wide AI pricing adoptions
 - The aggregate trend over time and variations across industries
 - The determinant factors of adopting at firm-level
 - The correlation between firm performances with adoption
- Today: Provide some causal evidence on AI pricing adoption and monetary transmission

Data and Measure

- We rely on Lightcast job posting data (2010-2024Q1) to identify (AI) pricing job posts
 - AI-related skills as the standard approach in Acemoglu et al. (2022b) and Babina et al. (2024)
 - Keyword "pricing" in job title (Scope 1), skill requirements (Scope 2), description (Scope 3)
 - Sum all scopes (non-overlapping) as the total AI pricing posts
- Merge to Compustat when documenting determinant factors and firm performances
- Merge to CRSP and Bauer and Swanson (2023) monetary shocks when documenting causal evidence
- Summaries omitted for today (to save time)

[The Rise of Al Pricing]

Aggregate Time Trends of AI Pricing, Pricing, and AI Jobs



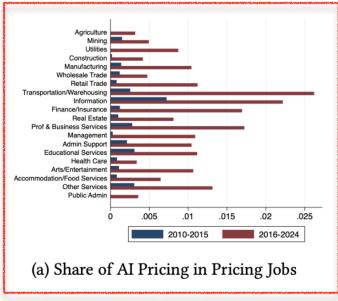
Leading Firms in AI Pricing Job Postings

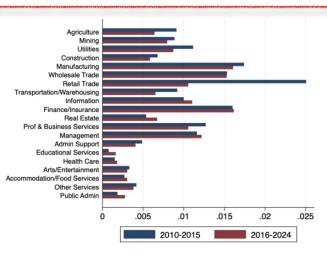
Firm	No. of AI Pricing Jobs	AI Pricing/AI Jobs	AI Pricing/Pricing Job
Deloitte	1672	6.9%	2.4%
Amazon	1198	1.7%	15.0%
Uber	664	21.1%	46.8%
Johnson & Johnson	611	8.5%	7.2%
Accenture	427	2.8%	2.0%
The RealReal	388	7.9%	43.6%
JPMorgan Chase	344	2.7%	2.8%
CyberCoders	337	0.9%	2.8%
USAA	281	7.7%	5.8%
Capital 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%

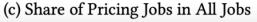
Variations Across Industries

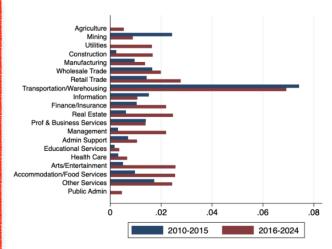
Al Pricing:

Transpotation
IT
Finance
Business Services
Retail
Education
Manufacuring
Entertainment

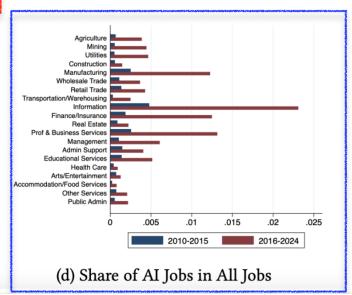








(b) Share of AI Pricing in AI Jobs



IT
Business Services
Finance
Manufacuring

AI:

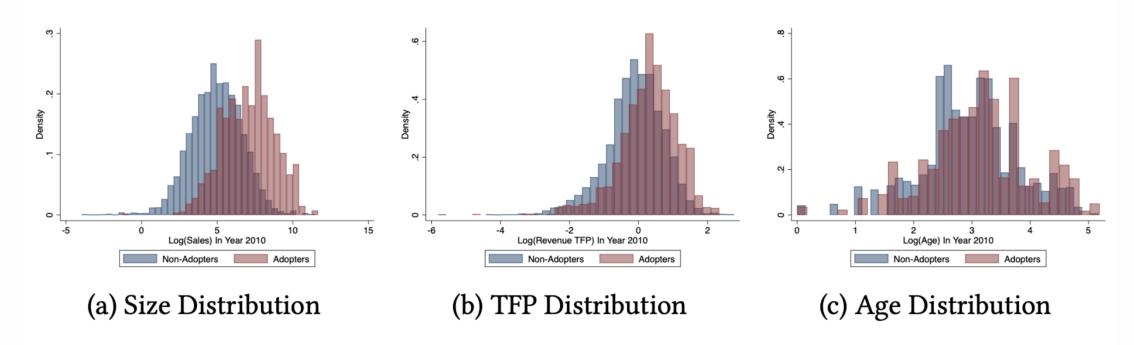
Takeaways

- A sharp rise of AI pricing jobs as a share of pricing jobs (0.12% to 1.34%)
- A (slow) decline of pricing jobs as a share of all jobs (0.93% to 0.59%)
 - Back of envelope calculation: AI pricing jobs \uparrow by $1 \Rightarrow$ Pricing jobs \downarrow by 50
- Firms who deal with more real-time pricing tasks tend to adopt more
- AI pricing jobs grew more rapidly and spread to broader industries
 - Including transportation, IT, business services, finance, and retail
 - While AI jobs are dominantly concentrated in IT

[Firm-level Determinants of Adoption]

Distributions of Adopters and Non-Adopters

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



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

Firm-level Determinants of AI Pricing Adoption

Table 4: Firm-level Determinants of AI Pricing Adoption

	711 1 11011	ig Haopter		ndicator, 2	010 2021	21 (± j,2024	Q1 - 1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.089***									0.109***
	(0.002)									(0.004)
Log TFP 2010		0.103***								0.024**
		(0.006)								(0.012)
Log Age 2010			0.032***							0.007
			(0.005)							(0.008)
Tobin's Q 2010				0.011***						0.006
				(0.003)						(0.004)
Log Markup					0.016**					0.009
					(0.007)					(0.016)
R&D/Sales 2010						-0.000				0.351***
						(0.000)				(0.065)
ROA 2010							-0.225***			0.130
							(0.081)			(0.136)
Cash/Assets 2010								-0.104***		0.020
5.1								(0.023)		(0.042)
Debt/Assets 2010									0.071***	-0.013
									(0.020)	(0.037)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	7768	7060	7304	7785	7748	3790	7776	7787	7299	3021
adj. R^2	0.205	0.060	0.022	0.018	0.017	0.021	0.017	0.004	0.002	0.239

Takeaways

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

[Al Pricing and Firm Performance]

Long-differences Results

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

	Δ Log Sales		Δ Log Employment		Δ Log	Assets	Δ Log Markup	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta APS_{j,[2010,2023]}$	1.193***	0.857***	0.996***	0.559**	1.134***	0.806***	0.259	0.282**
	(0.332)	(0.291)	(0.286)	(0.252)	(0.343)	(0.309)	(0.166)	(0.121)
Share of AI	tunners and the second second	-0.029	3004074780300000000000000	-0.332	**************************************	-0.237		-0.634**
		(0.663)		(0.570)		(0.706)		(0.277)
Share of Pricing		0.252		0.712***		0.321		-0.035
		(0.188)		(0.243)		(0.201)		(0.079)
Log Sales		-0.088***		-0.098***		-0.107***		0.005
		(0.009)		(0.008)		(0.009)		(0.004)
Log TFP		-0.014		0.118***		-0.013		-0.085***
		(0.020)		(0.018)		(0.021)		(0.008)
Log Age		-0.117***		-0.114***		-0.110***		0.003
		(0.016)		(0.014)		(0.017)		(0.007)
Tobin's Q		0.436***		0.360***		0.684***		-0.032**
		(0.035)		(0.032)		(0.038)		(0.015)
Cash/Assets		0.003		0.173*		-0.291***		0.184***
		(0.103)		(0.095)		(0.110)		(0.043)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4014	3583	3677	3293	4025	3587	4014	3583
adj. R^2	0.064	0.184	0.086	0.228	0.049	0.201	0.018	0.054

Long-differences Results

Table 8: AI Pricing and Heterogeneous Firm Performance: Long-differences

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

Evidence from High-frequency Monetary Shocks

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

- $R_{j,e}$ denotes the daily stock return of firm j in the event date e
- MP_e is our monetary shocks (sign-flipped, divided by 25 bps)
- $X_{j,t-1}$ denote the variables of interest (demeaned if are continuous), including
 - firm-level lagged AI pricing adoption dummy $1_{j,t-1}^{AP}$
 - firm-level lagged AI pricing adoption share $APS_{j,t-1}$
 - industry-level frequency of price adjustment FPA_s (standardized)

Evidence from High-frequency Monetary Shocks

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

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

Evidence from High-frequency Monetary Shocks

Table 12: Response of Stock Return 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)
$MP_e \times \text{Share of AI}$	10.855**	**************************************	***************************************	1449, 011,000,000,411,011,011,111,111,111			######################################		13.588***
	(4.608)								(4.702)
$MP_e \times \text{Share of Pricing}$		-2.934							-2.762
		(2.108)							(2.113)
$MP_e \times \text{Log Sales}$			-0.040						0.039
			(0.083)						(0.107)
$MP_e \times \text{Log Age}$				-0.133					-0.159
				(0.170)					(0.182)
$MP_e \times \text{Log TFP}$					-0.628***				-0.690***
					(0.164)				(0.251)
$MP_e \times \text{Log Tobin's Q}$						-0.598**			-0.239
						(0.253)			(0.311)
$MP_e \times \text{Cash/Asset}$							-1.351*		-0.889
							(0.775)		(1.016)
$MP_e \times \text{Log Markup}$								-0.556**	0.262
								(0.235)	(0.345)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	24432	24432	24432	24432	24432	24432	24432	24432	24432
adj. R^2	0.175	0.175	0.175	0.175	0.176	0.175	0.175	0.175	0.176

Increase APS from 0 to 10% is similar to increase FPA by 1 std

Takeaways

- Firms with more AI pricing are associated with higher growth and markup
- Firms with more AI pricing have larger stock returns upon monetary expansion
 - Just as if the firm is in an industry with more flexible prices
- Magnitude: from non-AI-pricing to Amazon (16%), responses increase by 33%
- Equivalent to an increase in the frequency of price adjustment by two standard deviations!

Remarks and In-progress

- AI pricing is rising rapidly and is widely adopted in broad industries
- Preliminary results show that it may act as reducing price stickiness in the aggregate
- In-progress: A sticky information model + AI pricing and BLS micro-pricing patterns