The Rise of AI Pricing:

Trends, Driving Forces, and Implications for Firm Performance

Jonathan Adams[1], Min Fang[2], Yajie Wang[3], Zheng Liu[4]

[1]FRB Kansas City; [2]University of Florida; [3]University of Missouri; [4]FRB San Francisco

Oct 3, 2025
Conference on Frontiers in Machine Learning and Economics
Center for Applied AI, Chicago Booth

*The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of San Francisco/Kansas City or the Federal Reserve System.

AI-powered pricing in the news

The Economist

Subscribe | Log in

Weekly edition | The world in brief | War in the Middle East | War in Ukraine | The world ec

Business | Surge pricing

How companies use AI to set prices

The pricing of products is turning from art into science

Subscribe To Newsletters

Forbes

Harnessing AI For Dynamic Pricing For Your Business

By Neil Sahota, Former Contributor. Neil Sahota is a globally sought after speaker and business advisor.

Jun 24, 2024, 10:28am EDT

Save Article | Comment 0

More companies have turned to AI for real-time dynamic pricing and revenue management. GETTY

THE WALL STREET JOURNAL.

Latest | World | Business | U.S. | Politics | Economy | Tech | Markets & Finance | Opinion | Arts | Lifestyle | **Real Estate**

REAL ESTATE

Big Cities Take Up Fight Against Algorithm-Based Rents

Lawmakers are under pressure to rein in housing costs

By Will Parker Follow

Nov. 19, 2024 5:30 am ET

Forbes | Subscribe: Less than $1.50/wk

BUSINESS > RETAIL

Personalizing Price With AI: How Walmart, Kroger Do It

By Bryan Pearson, Contributor. I cover the intersection of retail, loyalty and... | Follow Auth

Sep 07, 2021, 10:11am EDT

Background

- Recent rise of AI has spurred interest in studying macro effects of new technologies
  - Labor market, economic growth, income inequality, firm performance, market concentration, ...
- A lesser-known area is the rise of AI-powered algorithmic pricing (or AI pricing)
  - Unlike traditional price-setting, AI pricing uses advanced algorithms for predictive analysis of large data, incorporating real-time changes in market conditions

Background

- Recent rise of AI has spurred interest in studying macro effects of new technologies
    - Labor market, economic growth, income inequality, firm performance, market concentration, ...
- A lesser-known area is the rise of AI-powered algorithmic pricing (or AI pricing)
    - Unlike traditional price-setting, AI pricing uses advanced algorithms for predictive analysis of large data, 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 specific industries
    - online retailing (Wang et al., 2023), housing rental (Calder-Wang and Kim, 2023), gasoline (Assad et al., 2024), and online pharmaceuticals (Brown and MacKay, 2023)
- 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
    - Correlations with firm performance

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
- Examine how AI pricing affects sensitivity of firm stock returns to high-frequency monetary policy shocks

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
- Examine how AI pricing affects sensitivity of firm stock returns to high-frequency monetary policy shocks
- Present a simple model to rationalize stylized facts and monetary shock effects
  - A monopolist with imperfect information about demand invests in traditional pricing or AI pricing to acquire information
  - Model mechanism: AI pricing enhances price discrimination
  - Model predictions in line with stylized facts

Data and measurements

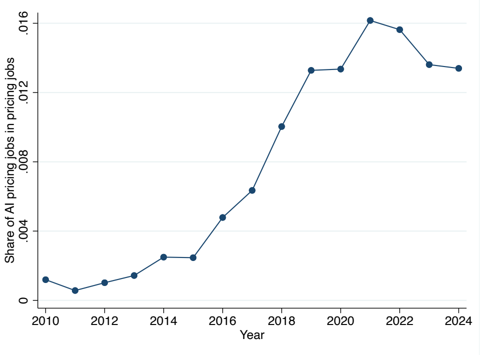
- Use online job postings data from Lightcast (2010-2024) to identify AI pricing jobs
    - First, identify jobs requiring AI skills using the ▸ narrow AI skill categories (Acemoglu et al., 2022)
    - Then, within set of AI-related jobs, search for the keyword “pricing"
    - AI-pricing job both requires AI-related skills *and* contains keyword “pricing"

Data and measurements

- Use online job postings data from Lightcast (2010-2024) to identify AI pricing jobs
    - First, identify jobs requiring AI skills using the ▸ narrow AI skill categories (Acemoglu et al., 2022)
    - Then, within set of AI-related jobs, search for the keyword “pricing"
    - AI-pricing job both requires AI-related skills *and* contains keyword “pricing"
- Aggregate AI-pricing job postings to firm level and merge with Compustat
    - Study firm-level determinants of adoptions
    - Examine correlations of AI pricing with firm performance
- Merge Lightcast/Compustat data with CRSP daily stock returns
    - Study how AI pricing affects responses of stock returns to monetary policy shocks

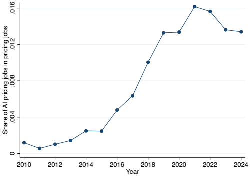
[The Rise of AI Pricing]

Aggregate trends of AI pricing jobs

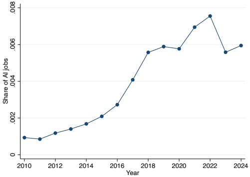


- Share of AI pricing jobs in all pricing jobs surged over 10 times (from 0.12% in 2010 to 1.34% in 2024), with most increases after 2015

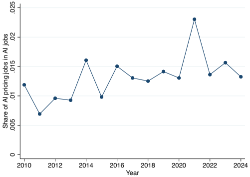
Aggregate trends of AI pricing, AI jobs, and pricing jobs



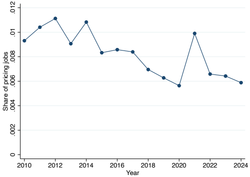
(a) Share of AI Pricing in Pricing Jobs



(b) Share of AI Jobs in All Jobs



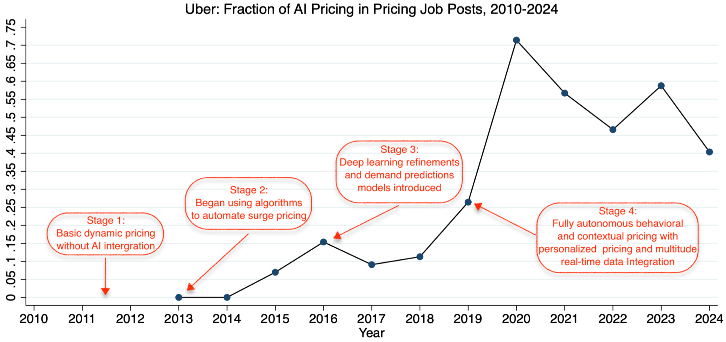
(c) Share of AI Pricing in AI Jobs



(d) Share of Pricing Jobs in All Jobs

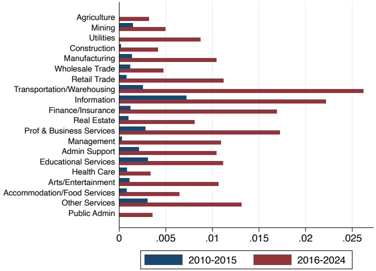
- The trend of AI pricing jobs parallels that of AI jobs
- While AI pricing rose by 10 times, overall share of pricing jobs fell by 40% since 2010

Evolution of AI pricing job posts: The case of Uber

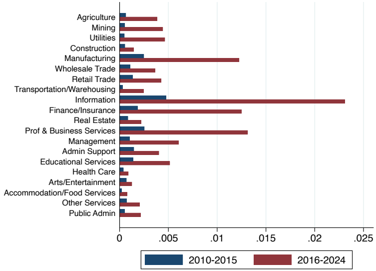


- Similar patters for Amazon and JP Morgan

Variations across industries: AI pricing vs. general AI



(a) Share of AI Pricing in Pricing Jobs



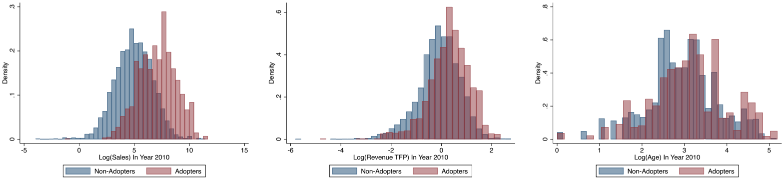
(b) Share of AI Jobs in All Jobs

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

[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

- Large, productive, and R&D intensive firms are more likely to adopt and adopt more
- Other factors such as age, financial or operational conditions not consistently important [See paper for details]

[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
- Correlations are stronger for larger firms ▸ Details

Effects of high-frequency monetary shocks

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

- $R_{j,e}$: daily stock return of firm j on event date e (percent, CRSP)
- MP_e: orthogonalized monetary policy surprises on event date e from Bauer-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, lags of pricing job share)
- Also consider average frequency of price adjustments FPA_s in NAICS 6-digit industry s (Pasten, et al 2020) and its interaction with MP_e
- Sample periods: Jan 2010 to Dec 2019

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

Asymmetric effects of AI pricing for monetary policy 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 from AI pricing is stronger for policy tightening than for easing

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 Antras, et al. (2012)
- Amplification effects concentrated in downstream firms, which are closer to consumers

[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

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

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

- Profit increases with market size (μ), aggregate demand ($\bar{z}$), markup (inversely related to η), and information about demand function ($R(N)$)
- Firm acquires information using basic pricing labor L_b or AI pricing labor L_a combined with computing equipment C
- AI pricing incurs fixed cost $\chi \rightarrow$ discrete adoption of AI pricing
- Optimal information acquisition decisions

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

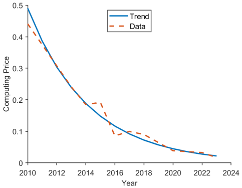
$$s.t. \quad N = L_b^{\beta} + (AL_a)^{\alpha} C^{\gamma}$$

Model predictions

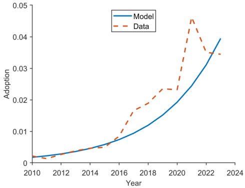
1. Adoption of AI pricing increases as computing price q falls (Prop 1)
2. Share of AI labor $\frac{L_a}{L_a+L_b}$ increases as q falls (Prop 2)
3. Given q, share of AI labor increases with firm size (revenue) (Prop 3)
4. Given q, the share of AI labor increases with firm markup (Prop 4)
5. Gross profit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

Model predictions in line with empirical evidence

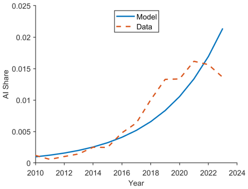
- Model simulated based on trends in GPU prices (q) with parameters $\beta = 0.75$, $\alpha = 0.6$, $\gamma = 0.2$, $A = 0.18$, $\Phi = 1$, $\rho = 1$, $\xi = 5$, $\mu_{min} = 0.15$.



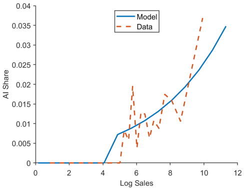
(a) AI Computing Cost



(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
- Evidence suggests that AI pricing increases firm profit and its sensitivity to monetary policy shocks, after controlling for effects of price flexibility
- Simple model suggests that AI pricing influences firm performance through price discrimination (learn about demand function)
- Next step: Use micro-PPI data to study causal effects of AI pricing adoption on 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

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%

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 $\times$ Szie Group FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N	4005	3777	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

Return