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AI Expectations and Outcomes

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Abstract Evaluating the accuracy of predictions about AI use and outcomes is important given their potential influence on policy and decision making. In this paper, we study whether businesses' expectations about their use of AI have translated into the desired outcomes. First, we use the U.S. Census Bureau's Business and Trends Outlook Survey for 2023–2026 to compare predictions of AI use with actual AI use to see how well businesses have been anticipating their true rate of AI adoption. We find a learning curve: AI adoption initially happened slower than expected, was followed by a short period of growth that was faster than expected, and more recently has been close to expected rates. Next, we see if the motivations for adopting AI translated to associated outcomes by combining data about the motivations of early AI adopters from the Census Bureau's 2019 Annual Business Survey with detailed data on output, inputs, and total factor productivity from the BEA-BLS Integrated Industry-Level Production Account. We find some evidence that stated motivations for using AI are linked to related changes in production processes; importantly, use cases for AI are associated with increased intensity of R&D use. This suggests that even if the link between motivations and outcomes is murky at this point, structural change may be in the planning process but not yet observed in the outcome data.

Keywords Artificial intelligence (AI), expectations, labor, automation, output, productivity

JEL codes O4, E01

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1. Introduction

Less than 20 percent of U.S. businesses reported using artificial intelligence (AI) in the first quarter of 2026, though adoption continues to grow steadily [US Census Bureau, 2026]. Given the current rate of AI use, the economic impact of AI is often discussed in terms of its future or expected use. Forecasts and predictions about the use of AI are important to effectively plan and prepare for the potentially transformative impact of AI on the economy. For example, recent papers have estimated that use of AI could raise annual total factor productivity (TFP) growth in the U.S. between 0.3–0.7 percentage points by 2035 [Filippucci et al., 2025] and that unemployment rates could reach 10 percent or more by 2030 because of AI [VandeHei and Allen, 2025]. Evaluating the accuracy of predictions about the use and outcomes of AI is important given their potential influence on policy and decision making.

In this paper, we investigate whether businesses' expectations about their use of AI translated into the predicted outcomes by analyzing survey responses spanning multiple years. We approach this analysis in two ways. The first approach is to look at surveys showing industry expectations of AI use 6 months into the future and compare those predictions to actual use 6 months later to see how well businesses anticipated their use of AI. We find that, on average, businesses predicted their future use of AI within 2 percentage points of actual use, though accuracy of predictions varied greatly across industries. Given the relatively low rates of AI use over the period, small absolute differences sometimes translated to significant differences in relative expectations about growth. For example, 5.6 percent of businesses were using AI in 2023q4 and 6.7 percent of businesses expected to use AI in the next 6 months, translating to expected relative growth of just under 20 percent. However, by 2024q2, actual use rose to only 5.8 percent of businesses, representing a modest 0.2 percentage point absolute increase and real relative growth of just under 4 percent. Between 2023 and 2025, businesses shifted from overestimating future AI use to underestimating it and by the end of 2025, businesses were very close to accurately estimating future use. These findings imply that AI adoption initially happened slower than expected, was followed by a short period of growth that was faster than expected, and more recently has been close to expected rates.

In our second approach, we look at the motivations businesses reported for adopting AI in 2016–2018, such as automating tasks performed by labor or expanding the range of goods or services, and compare those motivations to observed economic measures years later to see if the reasons for adopting AI eventually translated into outcomes. We find that motivations of early AI adopters were sometimes realized, though oftentimes we did not find clear linkages between AI adoption and the original motivation.

Our focus in this short paper is intentionally narrow on measuring AI expectations and related outcomes, but we do note that the role of expectations is of broad interest in economics and important for economic policy. One paper that may be helpful in interpreting some of our results is D'Acunto et al. [2021]. That paper suggests that expectation setting around prices may fail to account for broad macro economic trends. If that is the case for AI as well, the large macro economic shift toward interest in AI may also be introducing a wedge between firm level expectations and outcomes.

The results in this paper indicate businesses' expectations about their use of AI are not always realized in future outcomes. While our analysis suggests businesses may be getting better at anticipating their future use of AI, a longer time series of data is needed to confirm this trend. The uncertainty and inconsistency of businesses expectations about the use of AI should therefore be taken into account when forecasting and making decisions about the future economic impacts of AI. Relatedly, the analysis in this paper embeds a murky conceptual link between stated motivations for using AI and the economic outcomes that we are able to measure with currently available data. It is possible early adopters of AI did achieve some of their original goals, but we are unable to isolate the effects given the coarseness of the available data. Thus, an important future direction is to continue to develop relevant data for measuring the ongoing economic impact of AI.

2. Methodology

2.1. Measuring Expected AI Use and Actual AI Use

To examine how well businesses can predict their future use of AI, we use time series data from the 2023–2026 Business Trends and Outlook Survey (BTOS) from the U.S. Census Bureau (Census). The BTOS is a nationally representative survey sent to over 200,000 employer businesses every two weeks to gather information about current and projected business conditions. The BTOS is published by North American Industry Classification System (NAICS) industry at the two-digit or sector level.

Beginning September 2023, the BTOS has asked businesses two questions related to AI use every two weeks.[2] The first question asks whether the business used AI in the last two weeks and the second asks if the business thinks AI will be used during the next six months. To determine the accuracy of the projected AI use, we first aggregate biweekly responses to quarters by using the average fortnightly response for each industry. Then we compare the 6 month projected use value to the actual use reported two quarters later. For example, we compare the 2024q1 projected values of AI use in 6 months to the observed 2024q3 values of AI use in the last two weeks.

In late 2025, BTOS changed the survey questions that asked about current and future AI. The old ques-

[2] Due to the federal government shutdown in 2025, Census did not collect data for the reference periods covering October 6–November 16.

tion asked, "Did this business use Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)" The new question drops the language about production of goods or services and asks, "Did this business use Artificial Intelligence (AI) in any of its business functions?" This broader language resulted in reported AI usage almost doubling between surveys, creating a discontinuity that prevents a fair comparison. As a result, we do not compare usage predicted in 2025q2 and 2025q3 to actual use 6 months later when the question was changed.

2.2. Measuring the Motivations and Outcomes of Early AI Adopters

We start our examination of the motivations and outcomes of early AI adopters using data from the 2019 Annual Business Survey (ABS), conducted by the U.S. Census Bureau. The ABS asked businesses whether they used AI between 2016–2018 and, if so, what was their motivation for using the technology.[3] Businesses were given five options to choose from and were allowed to select multiple options. The choices were:

1. To automate tasks performed by labor
2. To upgrade outdated processes or methods
3. To improve quality or reliability of processes or methods
4. To expand the range of goods or services
5. To adopt standards and accreditation.

A general response of "some other reason" was also allowed. The data were published by NAICS industry at the two-digit level.

A goal of this analysis is to investigate whether industries that were motivated to adopt AI to reduce labor, increase productivity, and expand output eventually achieved those outcomes. We focus our analysis on the first four motivations because they can be connected to specific macroeconomic outcomes within the Integrated Industry-Level Production Account (ILPA), which is jointly produced by the U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor Statistics (BLS). The ILPA contains detailed data on output and inputs as well as TFP growth by industry. In the ILPA, industry-level output and intermediate inputs from BEA's Gross Domestic Product (GDP) by Industry Accounts are combined with capital input and labor data from the BLS Productivity Program.

[3] Acemoglu et al. [2022] provide a detailed description of the results of these AI questions and related technologies in "Automation and the Workforce: A Firm-level View from the 2019 Annual Business Survey."

We conduct a similar analysis as Highfill and Samuels [2026a] and Highfill and Samuels [2026b] that use difference-in-difference (DiD) models to parse out differences in outcomes based on an industry's relative use of AI. Instead of intensity of AI use, in this paper we are interested in whether, for example, labor grew relatively slower (or contracted relatively faster) in industries where the greatest motivation for adopting AI was to automate tasks performed by labor. We also test the other outcome variables available in the ILPA to provide any insights related to the original motivation. For example, we investigate whether industries motivated by automating labor had higher rates of capital investment.[4]

3. Results

3.1. Comparing Expected AI Use with Actual AI Use

In 2023q3, 5.0 percent of businesses reported using AI and 6.3 percent of businesses reported that they expected to use AI in the next 6 months (see table 1). Six months later, in 2024q1, only 5.7 percent of businesses reported using AI. In other words, a relative growth rate of 26.0 percent was expected, but only a modest 0.7 percentage point increase took place, resulting in a real relative growth rate of 14.0 percent. Businesses overestimated growth in AI use even more the following quarter. While firms predicted a relative growth rate of 19.6 percent, actual utilization rose from 5.6 percent to just 5.8 percent, a real relative increase of only 3.6 percent. In contrast, by 2025q1, expectations reversed and underestimated the change. During this period, 8.6 percent of businesses reported using AI and 9.9 percent expected to adopt it within six months, representing an anticipated relative growth of 15.1 percent. However, actual use by 2025q3 reached 11.6 percent; this realized relative growth of 34.9 percent was more than double what was originally expected. By 2025q4, 21.4 percent of businesses estimated they'd be using AI in 6 months, only 0.1 percentage point lower than the actual value of 21.5 percent in 2026q2.

Table 2 shows the sectors with the highest use of AI as of the end of 2025, ranging from 25.4 percent in the Real estate and rental and leasing sector to 39.6 percent in the Information sector. In 2025q4, 42.4 percent of businesses in the Information sector predicted they would be using AI within the next 6 months, very close to the actual value of 42.2 percent in 2026q2. This contrasted from the other high-use sectors that were off by an average of 2 percentage points. While the Educational services sector overestimated their future use, the other three high-use sectors underestimated. Businesses in the Professional, scientific, and technical services sector reported AI use of 35.3 percent in 2025q4, with expectations of AI use within 6 months to be 37.1 percent, a 5.1 percent growth rate. Instead, AI use grew 10.8 percent between 2025q4 and 2026q2. Finance and insurance underestimated by an

[4] We use the regression approach described in Highfill and Samuels [2026b] and also extend the industry dataset by one year. The updated data cover 1997–2024.

even greater amount–AI use was expected to grow by 5.0 percent in 6 months but it actually grew 15.5 percent.

To assess whether the tabulations reported above are statistically significant, we run a simple regression to test if the gap between expected and actual AI use has changed over time. The regression results confirm the following: 1) early in the sample period, while usage was relatively low, there was not a significant difference between expected AI usage 6 months out from the sample period and actual use for the period for which expectations were reported, 2) during the middle years of the sample, actual use of AI significantly exceeded expected use reported 6 months earlier, and 3) by the end of the sample, there was not a significant difference between the actual and expected use of AI across industries. This is consistent with a basic learning model that as businesses analyze their use cases for AI, expected and actual use of AI becomes more aligned.[5]

3.2. Macroeconomic Outcomes of Early AI Adopters

3.2.1. Summary Statistics

Among businesses that adopted AI in 2016–2018, the top two reported motivators were to improve quality or reliability of processes or methods (49.2 percent) and to upgrade outdated processes or methods (37.1 percent). The motivation to automate tasks performed by labor was cited by 27.5 percent of businesses, followed closely by the desire to expand the range of goods or services (23.8 percent). Many businesses indicated multiple motivations for adopting AI.

Table 3 shows each motivation with the industries that had the highest rates of choosing it as the reason for adoption. The most common motivation, to improve quality or reliability of processes or methods, was chosen by 87.0 percent of businesses that adopted AI in the Utilities sector, the highest rate across all motivations. This motivation was also chosen by 64.3 percent of businesses in the Management of companies sector. This sector shows up in the top five rankings across all four categories, suggesting these businesses were motivated by many factors to adopt AI.[6]

The motivation to upgrade outdated processes or methods clearly overlapped with the first motivation to improve quality. A similar share of businesses in the Management of companies sector chose this motivation (60.4 percent), as did businesses in the Manufacturing and Finance and insurance sectors. Automating tasks performed by labor was chosen by 69.4 percent of businesses in the Agriculture, forestry, fishing, and hunting sector. This is almost double the rate of the next most likely motivation

[5] The regression results are in the Appendix table.

[6] Management of companies also includes headquarter establishments, so this is not just stand-alone management businesses.

in this sector—36.6 percent for upgrading outdated processes or methods.

3.2.2. Regression Results

We test empirically whether the share of businesses interested in particular motivations for AI is related to economic outcomes within BEA's industry economic accounts (see tables 4-9). We first note that overall reported AI adoption is pretty low (see table 1), so the results should be interpreted conditionally. That is, conditional on a firm being within the small set of firms that are pursuing AI, how are their stated motivations related to measured industry-level growth. As noted earlier, the mapping between stated motivations and industry level variables is murky. Nevertheless, we conduct this exploratory research in part due to the findings in our earlier work that AI use was associated with measured changes in industry-level production processes. In our earlier work (Highfill and Samuels [2026a]), we found preliminary evidence that AI is productivity enhancing and input saving based on the production account variables included in the ILPA. These production account variables on the sources of industry-level output growth are not perfect proxies for the outcomes associated with the motivations for using AI that are included in the ABS. But, because the variables were useful in our earlier work, we rely on them again for examining the relationship between AI motivations and industry-level production.

We consider each motivation in turn. The first motivation we check is "To automate tasks performed by labor." There is a relatively clean link between this motivation and measured industry-level factor inputs that we have described in our previous paper. We do not find statistically significant evidence in our approach that this motivation is associated with a relative decline in the contribution of labor input to output growth across industries. The regression results indicate that this motivation is associated with a statistically significant increase in an industry's use of capital inputs (relative to industries that do not report this as their major motivation). At the 10 percent level of significance, research and development capital increased relative to other industries, and the relative increase in other capital was an important contributor to the result for total capital input. Interestingly, use of intermediate input services was lower in this set of industries in comparison to industries that did not report being motivated by automating tasks performed by labor. To the extent that intermediate services may include paid (outsourced) labor services, this result may indicate a significant relationship between the stated motivation and the industry-level changes in production processes.

The second motivation that we investigate is "To upgrade outdated processes or methods." The link between this motivation and our industry-level variables is not as clean, but we do find a statistically significant relationship between the industries that state this as a motivation and industry-level contributions of research and development capital. If the approach to updating processes is tied to research and development, this result could be interpreted as confirming the link between motivation and reorganization of production to meet that motivation. Furthermore, the significant decrease in measured

TFP for those industries that are classified as being motivated by upgrading processes could also be related to the relative increase in research and development intensity because increasing use of any factor of production in the short term may temporarily show up as a decline in measured TFP if the new production process requires some time to reformulate.

The third motivation is "To improve quality or reliability of processes or methods." With this motivation, there is not a compelling statistical relationship between the industries that have reported being interested in the motivation and the measures of change in production that we use. Like the motivation above, we estimate a statistically significant decline in measured TFP in this set of industries, and this could be tied to an attempt to increase reliability, but this is a murky relationship. For example, this motivation is associated with a statistically significant increase in materials. If measured TFP temporarily declined as a result of buying more materials, one could connect the motivation to improve quality or reliability with these regression results.

The final motivation that we investigate is "To expand the range of goods or services." This is another unclear link between the motivation and the industry level data because expanding the range of goods or services may be associated with increased output for example, an increase in labor to provide new items, increasing research and development to provide new products, or increases in measured TFP if a new range of services manifest in the data as increased output without increasing inputs. The regression results indicate that this motivation is associated with measured relative increases in both TFP growth and labor productivity growth. That is, industries that are relatively high in this motivation experienced relatively rapid TFP and labor productivity growth. Also, this same set of industries had a labor contribution (both college and non college labor) that was significantly less than the other sectors. Taken together, these results suggest that expanding the range of goods and services appears to be an important motivation and associated with significant changes in production processes across sectors.

Because the specific motivations above are narrow and there is overlap in the industries that report for each of these motivations, we run two more regressions that attempt to span the motivations. The first is a composite that treats any sector as being motivated to use AI for a specific goal if it is in the top of any of the four stated specific AI motivations. This leads to 10 of the 19 sectors being classified as relatively motivated for an identified use case. With this composite, we find that industries that were motivated based on this categorization had a decline in the contribution of labor input relative to the others, and had significantly higher contributions of research and development capital. This composite provides evidence that while each motivation may not easily be tied to economic outcomes, taken together, use cases for AI are associated with important changes in production processes. That is, conditional on reporting using AI, having goals that span these four basic motivations is associated with measured structural change.

Finally, we construct a composite that takes sectors that are in the top groups for more than two motivations. For example, Management of companies is a top AI-motivated sector for each of the four, thus selected, as is Information because it is a top industry in three of the four. This composite is intended to capture sectors that have relatively strong motivations across those that we track and results in three of the 19 sectors being included as AI motivated. The results for these multiple top motivations indicate a relative increase in capital use, in particular research and development capital and a decrease in use of intermediate inputs, when overall AI motivation is based on appearing as a top industry in more than two specified motivations.

4. Discussion

In this paper, we analyzed survey responses over time to investigate whether businesses' expectations about their use of AI translated into related outcomes. On average, we find that after years of misaligned expectations, businesses appear to be better at anticipating future use of AI as of the end of 2025, consistent with a learning curve for AI. However, some industries with the highest use of AI continue to underestimate their future use as of 2026q2. If forecasted AI use has been underestimated in recent years and continues to be underestimated in important industries, then predictions about the future impact of AI could be understating potential effects.

We also analyzed the motivations of early adopters of AI from 2018 to see if their goals were eventually met. We find mixed results across the motivations that we are able to tabulate, but there is evidence that expectations and planning around the use of AI is related to changes to industry-level production processes, in particular increased use of R&D capital services. This suggests that even if the link between motivations and outcomes is murky at this point, structural change may be in the planning process but not yet observed in the outcome data. Similar to Acemoglu et al. [2022], we did not find a correlation between labor productivity growth and most of the motivations for adopting AI, with the exception of industries that were motivated to expand their range of goods and services. This may indicate that the relationship between adoption of AI and productivity growth is conditional on the original motivation of the adopting firm.

The goal of this paper was to evaluate expectations about the use of AI with currently available data. We were able to identify some interesting trends, but the lack of detail available in existing data means our results may not be robust and sometimes are inconclusive. Future research would benefit from more detailed data on industries and geography or, ideally, panel data to track firms actual AI use and the economic production processes for the same set of firms.

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Tables

Table 1. Share of Businesses Using AI and the Share Expecting to Use AI Within Six Months

	2023q3	2023q4	2024q1	2024q2	2024q3	2024q4	2025q1	2025q2	2025q3	2025q4	2026q1	2026q2
AI use	5.0	5.6	5.7	5.8	6.8	7.6	8.6	10.2	11.6	19.5	20.2	21.5
Expected AI use in 6 months	6.3	6.7	6.6	6.8	8.1	9.1	9.9	11.4	13.7	21.4	22.0	23.1
Actual growth in 6-month AI use			14.0	3.6	19.3	31.0	26.5	34.2	34.9	-	-	10.3
Expected growth in 6-month AI use			26.0	19.6	15.8	17.2	19.1	19.7	15.1	11.8	18.1	9.7

Source: Author’s calculations based on Census Bureau’s Business Trends and Outlook Survey

Note: A survey question change in 2025q4 created a break in the time series and prevents a fair comparison of growth in 2025q4 and 2026q1

Table 2. Share of Businesses Using AI and the Share Expecting to Use AI Within Six Months, Sectors with the Highest AI Use as of 2025q4

NAICS sector	AI use in 2025q4	Projected AI use in 6 months as of 2025q4	AI use in 2026q2	Actual growth in 6-month AI use	Expected growth in 6-month AI use
51-Information	39.6	42.4	42.2	6.6%	7.1%
54-Professional, scientific, and technical services	35.3	37.1	39.1	10.8%	5.1%
61-Educational services	33.0	36.4	34.8	5.5%	10.3%
52-Finance and insurance	31.7	33.3	36.6	15.5%	5.0%
53-Real estate and rental and leasing	25.4	27.1	28.4	11.8%	6.7%

Source: Author's calculations based on Census Bureau's Business Trends and Outlook Survey

Table 3. Motivations for Adopting AI in 2018 by NAICS Sector (Percent of Businesses)

Improve quality or reliability of processes or methods	Upgrade outdated processes or methods
22-Utilities, 87.0%	55-Management of companies, 60.4%
55-Management of companies, 64.3%	31-33-Manufacturing, 47.2%
52-Finance and insurance, 56.0%	61-Educational services, 43.8%
31-33-Manufacturing, 55.6%	52-Finance and insurance, 43%
62-Health care and social assistance, 54.5%	51-Information, 42.4%
Automate tasks performed by labor	**Expand the range of goods or services**
11-Agriculture, forestry, fishing, & hunting, 69.4%	51-Information, 38.2%
55-Management of companies, 52.4%	44-45-Retail trade, 30.1%
22-Utilities, 42.9%	55-Management of companies, 28.0%
31-33-Manufacturing, 38.4%	54-Professional, scientific, & technical services, 27.0%
51-Information, 37.6%	61-Educational services, 26.2%

Source: Census Bureau’s Annual Business Survey, 2019

Table 4. Regression Results Motivation: "To automate tasks performed by labor"

	VARIABLES	Interaction Term		Constant		R-squared
(1)	TFP	-0.679	(0.641)	0.534***	(0.0315)	0.094
(2)	ALP	-0.275	(0.683)	1.514***	(0.0336)	0.154
(3)	GO	-1.507**	(0.573)	1.776***	(0.0282)	0.326
(4)	Capital	0.306**	(0.117)	0.471***	(0.00574)	0.514
(5)	Labor	-0.436	(0.277)	0.262***	(0.0136)	0.372
(6)	Intermediate	-0.697	(0.742)	0.509***	(0.0365)	0.197
(7)	TFP	-0.679	(0.641)	0.534***	(0.0315)	0.094
(8)	Communications Equip.	-0.00955	(0.0244)	0.0461***	(0.00120)	0.881
(9)	Computer	0.0357	(0.0220)	0.0589***	(0.00108)	0.357
(10)	Instruments	0.0143**	(0.00610)	0.00869***	(0.000300)	0.704
(11)	Other Equip.	0.0717*	(0.0362)	0.0495***	(0.00178)	0.362
(12)	Structures, Land, Invent	0.0490	(0.0370)	0.0920***	(0.00182)	0.277
(13)	Transportation Equip.	0.1000	(0.0612)	0.0335***	(0.00301)	0.331
(14)	College Labor	-0.243	(0.154)	0.306***	(0.00760)	0.296
(15)	Non college Labor	-0.193	(0.130)	-0.0438***	(0.00640)	0.368
(16)	Energy	-0.0565	(0.107)	-0.0409***	(0.00529)	0.089
(17)	Entertainment Orig.	-0.0276	(0.0264)	0.0169***	(0.00130)	0.764
(18)	IT Hardward	0.0263	(0.0405)	0.105***	(0.00199)	0.602
(19)	Materials	0.592*	(0.290)	-0.120***	(0.0143)	0.219
(20)	Non college Labor	-0.193	(0.130)	-0.0438***	(0.00640)	0.368
(21)	Other Capital	0.235**	(0.0951)	0.184***	(0.00468)	0.329
(22)	Services	-1.232**	(0.533)	0.670***	(0.0262)	0.124
(23)	Research and development	0.0321*	(0.0167)	0.0646***	(0.000820)	0.778
(24)	Software	0.0398	(0.0608)	0.100***	(0.00299)	0.709

Table 5. Regression Results Motivation: "To upgrade outdated processes or methods"

	VARIABLES	Interaction Term		Constant		R-squared
(1)	TFP	-1.070*	(0.556)	0.557***	(0.0294)	0.095
(2)	ALP	0.401	(0.830)	1.479***	(0.0438)	0.154
(3)	GO	-0.999	(0.696)	1.754***	(0.0368)	0.325
(4)	Capital	0.215	(0.133)	0.474***	(0.00703)	0.513
(5)	Labor	-0.526*	(0.278)	0.268***	(0.0147)	0.373
(6)	Intermediate	0.383	(0.799)	0.455***	(0.0422)	0.197
(7)	TFP	-1.070*	(0.556)	0.557***	(0.0294)	0.095
(8)	Communications Equip.	-0.0126	(0.0232)	0.0463***	(0.00123)	0.881
(9)	Computer	0.0101	(0.0272)	0.0602***	(0.00144)	0.357
(10)	Instruments	0.00980	(0.00576)	0.00888***	(0.000304)	0.702
(11)	Other Equip.	0.0946**	(0.0344)	0.0480***	(0.00182)	0.365
(12)	Structures, Land, Invent	-0.000220	(0.0433)	0.0944***	(0.00229)	0.277
(13)	Transportation Equip.	0.0300	(0.0731)	0.0368***	(0.00386)	0.328
(14)	College Labor	-0.292*	(0.155)	0.309***	(0.00821)	0.297
(15)	Non college Labor	-0.234*	(0.131)	-0.0410***	(0.00692)	0.368
(16)	Energy	-0.0382	(0.114)	-0.0417***	(0.00600)	0.089
(17)	Entertainment Orig.	-0.0264	(0.0244)	0.0170***	(0.00129)	0.764
(18)	IT Hardward	-0.00248	(0.0447)	0.106***	(0.00236)	0.602
(19)	Materials	0.699**	(0.251)	-0.127***	(0.0132)	0.219
(20)	Non college Labor	-0.234*	(0.131)	-0.0410***	(0.00692)	0.368
(21)	Other Capital	0.134	(0.112)	0.188***	(0.00590)	0.326
(22)	Services	-0.278	(0.748)	0.624***	(0.0395)	0.122
(23)	Research and development	0.0447***	(0.0142)	0.0639***	(0.000750)	0.779
(24)	Software	0.0645	(0.0605)	0.0988***	(0.00319)	0.709

Table 6. Regression Results Motivation: "To improve quality or reliability of processes or methods"

	VARIABLES	Interaction Term		Constant		R-squared
(1)	TFP	-1.099*	(0.542)	0.557***	(0.0277)	0.095
(2)	ALP	-0.201	(0.700)	1.511***	(0.0357)	0.154
(3)	GO	-0.852	(0.723)	1.745***	(0.0369)	0.325
(4)	Capital	0.235*	(0.132)	0.474***	(0.00671)	0.513
(5)	Labor	-0.293	(0.278)	0.255***	(0.0142)	0.372
(6)	Intermediate	0.305	(0.775)	0.459***	(0.0395)	0.197
(7)	TFP	-1.099*	(0.542)	0.557***	(0.0277)	0.095
(8)	Communications Equip.	0.0252	(0.0166)	0.0444***	(0.000844)	0.882
(9)	Computer	0.0214	(0.0254)	0.0596***	(0.00130)	0.357
(10)	Instruments	0.00623	(0.00665)	0.00908***	(0.000339)	0.701
(11)	Other Equip.	0.0908**	(0.0359)	0.0484***	(0.00183)	0.365
(12)	Structures, Land, Invent	0.0427	(0.0377)	0.0922***	(0.00192)	0.277
(13)	Transportation Equip.	0.0242	(0.0732)	0.0372***	(0.00373)	0.328
(14)	College Labor	-0.133	(0.157)	0.301***	(0.00799)	0.295
(15)	Non college Labor	-0.159	(0.130)	-0.0452***	(0.00665)	0.368
(16)	Energy	-0.0202	(0.112)	-0.0427***	(0.00569)	0.089
(17)	Entertainment Orig.	0.0133	(0.0190)	0.0149***	(0.000969)	0.763
(18)	IT Hardward	0.0467	(0.0355)	0.104***	(0.00181)	0.603
(19)	Materials	0.646**	(0.266)	-0.123***	(0.0136)	0.219
(20)	Non college Labor	-0.159	(0.130)	-0.0452***	(0.00665)	0.368
(21)	Other Capital	0.164	(0.109)	0.187***	(0.00554)	0.327
(22)	Services	-0.321	(0.742)	0.625***	(0.0379)	0.122
(23)	Research and development	0.0252	(0.0184)	0.0649***	(0.000937)	0.778
(24)	Software	-0.0143	(0.0477)	0.103***	(0.00243)	0.708

Table 7. Regression Results Motivation: To expand the range of goods or services

	VARIABLES	Interaction Term		Constant		R-squared
(1)	TFP	1.566***	(0.488)	0.472***	(0.00889)	0.095
(2)	ALP	2.212***	(0.514)	1.460***	(0.00936)	0.156
(3)	GO	-0.800	(0.752)	1.716***	(0.0137)	0.325
(4)	Capital	-0.00743	(0.173)	0.486***	(0.00315)	0.511
(5)	Labor	-0.884***	(0.197)	0.257***	(0.00358)	0.374
(6)	Intermediate	-1.475**	(0.536)	0.502***	(0.00976)	0.198
(7)	TFP	1.566***	(0.488)	0.472***	(0.00889)	0.095
(8)	Communications Equip.	-0.0568	(0.0368)	0.0467***	(0.000670)	0.883
(9)	Computer	-0.0461	(0.0304)	0.0615***	(0.000553)	0.357
(10)	Instruments	-0.00147	(0.00983)	0.00943***	(0.000179)	0.701
(11)	Other Equip.	0.0554	(0.0422)	0.0520***	(0.000768)	0.360
(12)	Structures, Land, Invent	-0.0580*	(0.0276)	0.0954***	(0.000503)	0.277
(13)	Transportation Equip.	0.0523	(0.0499)	0.0375***	(0.000909)	0.328
(14)	College Labor	-0.521***	(0.113)	0.303***	(0.00205)	0.298
(15)	Non college Labor	-0.363***	(0.100)	-0.0467***	(0.00183)	0.369
(16)	Energy	-0.134	(0.0866)	-0.0412***	(0.00158)	0.089
(17)	Entertainment Orig.	-0.0638	(0.0443)	0.0167***	(0.000806)	0.767
(18)	IT Hardward	-0.103**	(0.0412)	0.108***	(0.000750)	0.604
(19)	Materials	-0.248	(0.279)	-0.0860***	(0.00508)	0.218
(20)	Non college Labor	-0.363***	(0.100)	-0.0467***	(0.00183)	0.369
(21)	Other Capital	0.0482	(0.102)	0.194***	(0.00186)	0.325
(22)	Services	-1.092*	(0.531)	0.629***	(0.00968)	0.123
(23)	Research and development	0.0412	(0.0239)	0.0655***	(0.000435)	0.778
(24)	Software	0.0703	(0.128)	0.101***	(0.00233)	0.709

Table 8. Regression Results Composite 1

	VARIABLES	Interaction Term		Constant		R-squared
(1)	TFP	-0.246	(0.719)	0.518***	(0.0511)	0.093
(2)	ALP	1.053	(0.724)	1.426***	(0.0514)	0.155
(3)	GO	-1.549*	(0.789)	1.812***	(0.0560)	0.326
(4)	Capital	0.248	(0.179)	0.468***	(0.0127)	0.513
(5)	Labor	-0.828***	(0.280)	0.299***	(0.0199)	0.375
(6)	Intermediate	-0.723	(0.868)	0.526***	(0.0616)	0.197
(7)	TFP	-0.246	(0.719)	0.518***	(0.0511)	0.093
(8)	Communications Equip.	-0.00580	(0.0173)	0.0460***	(0.00123)	0.881
(9)	Computer	-0.000302	(0.0284)	0.0607***	(0.00202)	0.356
(10)	Instruments	0.00626	(0.00687)	0.00895***	(0.000488)	0.701
(11)	Other Equip.	0.112**	(0.0419)	0.0451***	(0.00298)	0.367
(12)	Structures, Land, Invent	0.0255	(0.0534)	0.0926***	(0.00379)	0.277
(13)	Transportation Equip.	0.0606	(0.0915)	0.0341***	(0.00650)	0.328
(14)	College Labor	-0.454***	(0.150)	0.326***	(0.0106)	0.299
(15)	Non college Labor	-0.374**	(0.144)	-0.0268**	(0.0102)	0.370
(16)	Energy	-0.120	(0.147)	-0.0352***	(0.0105)	0.089
(17)	Entertainment Orig.	-0.0231	(0.0185)	0.0172***	(0.00131)	0.763
(18)	IT Hardward	-0.00608	(0.0412)	0.107***	(0.00293)	0.602
(19)	Materials	0.398	(0.295)	-0.119***	(0.0209)	0.218
(20)	Non college Labor	-0.374**	(0.144)	-0.0268**	(0.0102)	0.370
(21)	Other Capital	0.204	(0.144)	0.181***	(0.0103)	0.328
(22)	Services	-1.002	(0.708)	0.680***	(0.0503)	0.123
(23)	Research and development	0.0471***	(0.0145)	0.0629***	(0.00103)	0.779
(24)	Software	0.0263	(0.0420)	0.100***	(0.00298)	0.708

Table 9. Regression Results Composite 2

	VARIABLES	Interaction Term		Constant		R-squared
(1)	TFP	-0.905	(0.576)	0.540***	(0.0252)	0.094
(2)	ALP	-0.390	(0.677)	1.517***	(0.0296)	0.154
(3)	GO	-1.399**	(0.547)	1.763***	(0.0239)	0.325
(4)	Capital	0.266**	(0.108)	0.474***	(0.00470)	0.513
(5)	Labor	-0.390	(0.271)	0.258***	(0.0119)	0.372
(6)	Intermediate	-0.370	(0.692)	0.491***	(0.0303)	0.197
(7)	TFP	-0.905	(0.576)	0.540***	(0.0252)	0.094
(8)	Communications Equip.	-0.0138	(0.0284)	0.0462***	(0.00124)	0.882
(9)	Computer	0.0309	(0.0210)	0.0593***	(0.000920)	0.357
(10)	Instruments	0.00975*	(0.00540)	0.00897***	(0.000236)	0.702
(11)	Other Equip.	0.0748**	(0.0336)	0.0497***	(0.00147)	0.363
(12)	Structures, Land, Invent	0.0190	(0.0365)	0.0935***	(0.00159)	0.277
(13)	Transportation Equip.	0.0904	(0.0563)	0.0345***	(0.00246)	0.330
(14)	College Labor	-0.212	(0.151)	0.303***	(0.00658)	0.296
(15)	Non college Labor	-0.178	(0.127)	-0.0456***	(0.00555)	0.368
(16)	Energy	-0.0406	(0.0997)	-0.0419***	(0.00436)	0.089
(17)	Entertainment Orig.	-0.0300	(0.0307)	0.0169***	(0.00134)	0.764
(18)	IT Hardward	0.0172	(0.0439)	0.106***	(0.00192)	0.602
(19)	Materials	0.757***	(0.232)	-0.124***	(0.0102)	0.219
(20)	Non college Labor	-0.178	(0.127)	-0.0456***	(0.00555)	0.368
(21)	Other Capital	0.194**	(0.0878)	0.187***	(0.00384)	0.328
(22)	Services	-1.087**	(0.511)	0.657***	(0.0223)	0.123
(23)	Research and development	0.0430***	(0.0143)	0.0644***	(0.000627)	0.779
(24)	Software	0.0423	(0.0680)	0.100***	(0.00297)	0.709

Appendix

This appendix includes the regression results mentioned in the main text but not included.

The first regression is on the gap between actual AI use for the period to which the reported expectation corresponds. A positive coefficient indicates that actual use for the period exceeded the expectation for the same period. By the end of the sample (2025q4), there was not a statistically significant difference between expectation for the period and the actual. Each observation is an industry, quarter difference.

	(1)
VARIABLES	diff
year_qtr = 20234	-0.356
	(0.608)
year_qtr = 20241	0.834
	(0.608)
year_qtr = 20242	1.301**
	(0.608)
year_qtr = 20243	0.770
	(0.608)
year_qtr = 20244	1.585**
	(0.608)
year_qtr = 20251	2.121***
	(0.608)
year_qtr = 20254	0.395
	(0.616)
Constant	-0.280
	(0.435)
Observations	150
R-squared	0.156

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$