Early Evidence on the Relationship Between AI, Costs, and Prices Within BEA's Industry Economic Accounts

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Abstract In previous work, Highfill and Samuels [2026], we explored the relationship between AI and the sources of U.S. economic growth. In this paper, we investigate the relationship between AI adoption, production costs, and output prices. We find that AI intensity is associated with lower prices charged to purchasers, and some of this reduced price is related to reduced input cost contributions, in particular labor and materials costs.

Keywords Artificial intelligence (AI), prices, cost structure

JEL Code E31, D24, O33

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The views expressed in this paper are those of the authors and do not necessarily represent the U.S. Bureau of Economic Analysis, or the U.S. Department of Commerce.

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1. Introduction

The economic mechanisms that relate the use of artificial intelligence (AI) to costs and prices are complex, involving gestational lags and tradeoffs between adoption costs and potential gains in efficiency. Parsing these effects out in the macroeconomic data is a difficult exercise, but the economic intuition for many of the potential relationships is relatively straightforward. If a firm is able to economize on the use of other inputs as a result of the use of AI, the decrease in demand for those inputs may impact the price of that input. Furthermore, if said firm operates in a competitive environment, those price and cost reductions would likely be passed on to purchasers, i.e., prices paid by consumers or other businesses. Of course, the economic realities and adjustments to new technologies are not as seamless as a frictionless, perfect-foresight, competitive economic model would predict. Thus, we do not attempt to formulate a structural economic model to capture the many potential tradeoffs that are introduced with the application of AI, but investigate macroeconomic outcomes empirically using currently available economic data. In particular, we ask the question: is the deployment of AI associated with observed measures of changes in prices of inputs and outputs within the current version of BEA's industry economic accounts?

Theoretically, the relationship between AI and prices could go in either direction, especially in the shorter run. For example, if AI is expensive to employ and requires advanced engineers and equipment, along with drawing a significant amount of energy from the grid, AI may be associated with increased output prices that producers need to charge to recover those costs. Because deployment of AI requires significant investment in non-residential structures like data centers, it is certainly theoretically possible that early adoption of AI is associated with increasing costs and prices. On the other hand, deployment of AI could lead to reduced costs and prices, as discussed above.

In this paper, we are interested in early empirical evidence on the relationship between AI, costs, and prices at the macroeconomic level and how those relationships would (potentially) be observable in the U.S. national accounts. Thus, we frame the question about the relationship between AI and prices within the currently available BEA-BLS Integrated Industry-Level Production Account (ILPA). With some simple manipulation, this account shows the industry-level sources of price growth in the U.S. economy and how changes in the prices of factors of production relate to changes in purchaser prices. An objective of this paper is to discuss how these prices are measured, their potential relationship to the use of AI, measurement challenges that may be pertinent, and to conduct a simple empirical exercise that examines the relationship between the use of AI and price change.

2. Where This Paper Fits

We take it as given that there is general and widespread interest in the economic impact of AI, so we do not preface our analysis with extensive motivation. Furthermore, we do not attempt to review the large

and growing literature on the economics of AI. We note that while there are many papers and articles that speculate about the relationship between AI, costs, and prices, to the best of our knowledge, there is not an existing economics research paper that examines this relationship using data within the U.S. national accounts. Examining AI within the framework of the national accounts ensures consistency with the official gross domestic product (GDP) and productivity measures.

We do point readers to our previous paper about the relationship between AI intensity and economic growth, Highfill and Samuels [2026]. That paper focuses on the relationship between AI and the real side of the economy (for example, how AI intensity is related to productivity and real contributions of the factors of production to industry output growth). It also includes additional background information on economic measurement, our AI-intensity measure, and the econometric approach that we also use in this paper.

3. Background on Cost and Price Data

To estimate how AI interacts with costs and prices, we need measures of AI intensity and relevant prices. We use the AI-intensity measures developed in Highfill and Samuels [2026]; thus, we do not describe the detailed construction of the dataset here, but just note that we classify industries into quartiles based on the intensity of their AI used as reported in Census survey data. Thus, our AI indicator is a relative measure, and our results should be interpreted as comparisons between these AI-intensive industries and the remainder, not as absolute measures of the impact of AI. We view these as exploratory benchmarks and indicators.

The costs and price measures that we use in this paper are based on the ILPA. These measures are particularly relevant because they are constructed to be consistent with the real GDP by industry measures that underlie official real aggregate value-added growth. Thus, our measures are also consistent with the official U.S. national accounts. We augment the GDP by industry prices to include price deflators for labor and capital services that are used to formulate the real measures of input growth in the ILPA. An intuitive way to think about the price indexes that we use is that these measures form the basis for measuring the cost function of each industry in the economy. The ILPA data that were used to estimate the relationship between AI and the sources of economic growth in Highfill and Samuels [2026] were production function data. In the exercise in this paper, we use the price deflators from that dataset, and these capture the cost function for each industry.

Specifically, for each industry in the ILPA, we construct implicit price indexes as the ratio of nominal to chain-type quantity index, for each industry's output and inputs. Then, we conduct a price accounting exercise (dual to growth accounting) that attributes growth in each industry's gross output price to the contribution of labor, capital, and intermediate input prices. Capital is subdivided into five types of capital services: information technology equipment, research and development, software, entertainment

originals, and other capital. Labor prices are split into prices for workers with a BA degree and above (college workers) and those without a BA degree (non-college workers). Intermediate input prices are decomposed into prices for energy, materials, and services.[2] The remainder of industry price change not accounted for by the contribution of input prices is price change associated with total factor productivity (TFP) growth (all else equal an increase in TFP growth yields a decrease in industry output prices). The intuition for this is that if a producer can charge lower prices when its input prices have gone unchanged, this must be due to an improvement in its production process (TFP).

To be specific, our data are based on a price-cost function for each industry:

$$\Delta \ln P_{Y,it} = \underbrace{\sum_{k} \bar{w}_{K_k,it} \Delta \ln p_{K_k,it}}_{\text{Capital Price Contr.}} + \underbrace{\sum_{l} \bar{w}_{L_l,it} \Delta \ln p_{L_l,it}}_{\text{Labor Price Contr.}} + \sum_{m} \bar{w}_{M_m,it} \Delta \ln p_{M_m,it} - \Delta \ln TFP_{it} \quad (1)$$

The left-hand side is each industry's output price growth. The right-hand side is the contribution of the price of each input, including k types of capital, l types of labor, and m types of intermediate input.

In this early-stage research, we test the relationship of AI intensity with nominal value shares of each input, the w terms in the above equation. We think about these regressions as capturing the relationship between AI and cost structure, for example if AI intensity is associated with an increase or decrease in the labor share, that is informative about structural change in the economy.

To assess the relationship between AI and prices, we use the above equation to define contributions of each price to industry gross output price change:

$$Cont_{j,it} = \bar{\omega} j, it \Delta \ln pj, it = \frac{1}{2} \left(\frac{V_{j,it}}{V_{GO,it}} + \frac{V_{j,it-1}}{V_{GO,it-1}} \right) (\ln p_{j,it} - \ln p_{j,it-1}) \quad (2)$$

That is, for each input j, the contribution of its price change to gross output price change is its log growth times its two-period nominal value share. While this is standard in the growth (price) accounting literature, in this paper, we relate these contributions to AI intensity by industry. This contribution variable summarizes the interaction between cost structure and price change, so if, for example, AI intensity is associated with a relatively lower contribution of labor input prices, this reflects potentially both an industry shifting its cost structure *and* the equilibrium effect of AI and wages *relative* to less AI intensive industries.

[2] A contribution is defined using a tornqvist index and a nominal share weighted log growth rate.

4. Overview of the Econometric Model and Baseline Results

We use the same difference-in-difference model described in Highfill and Samuels [2026] but with prices and costs as left-hand side variables instead of the variables capturing real contributions to economic growth that were analyzed in that paper.

We run regressions of the form:

$$y_{it} = \alpha_i + \gamma_t + \beta(D_s \times Post_t) + \epsilon_{it}$$

where y_{it} is one of industry-level variables for the 61 private sector industries, α_i is an industry-level fixed effect, γ_t is a year effect, and the interaction of interest is the coefficient on the $(D_s \times Post_t)$ variable, which is the interaction of the AI-intensity indicator at the 19 sector level and the 2022 and 2023 year indicator. Years before 2022, i.e. between 1997 and 2021, are deemed to be years without significant use of AI. We use the estimation strategy in Borusyak et al. [2024] to circumvent some of the challenges of off-the-shelf OLS; one particular advantage of the Borusyak et al. [2024] method is that it uses an imputation method to predict the trend in variables and then tests how AI intensity impacts that trend. Standard errors are clustered at the 19 sector level to correspond to the AI-intensity measures.

We analyze the interaction of AI intensity and both prices and cost shares. The regressions on cost shares capture potential substitution effects related to the interaction of AI with input usage and the regressions on price growth capture the overall interaction between supply and demand of factors of production and prices.

Summary statistics for our variables on cost and price are given in Table 1. We do not review the properties of every variable in the table, but one way to motivate our empirical exercise is to examine the difference between the column "AI Pre 2022" and "AI Post 2021." The difference between the two is the change, for AI-intensive industries, starting in 2022, and our regression model tests whether this change is statistically significant. For example, the capital share in gross output for AI-intensive industries was about 27.1% before 2022 and 28.5% in 2022 and 2023, on average. This preliminary exercise seeks to characterize whether the 28.5% is related to the use of AI. For the change in the share variables, the "D" variables, the model asks of the data whether the change (first difference) in the share is related to the intensity of AI use at the industry level. For the price variables, for example, the gross output price, the summary table shows that output prices for AI-intensive industries grew by about 2.3% per year after 2021, while output prices for non-AI-intensive industries grew by about 5.6% per year. The model that we run tests econometrically whether these tabulated price differences are related to AI in a statistically significant way. Importantly, these tabulated prices do not correspond to aggregate measured inflation in the U.S. economy over this period, partly because these prices are not weighted by value shares (each industry is weighted equally) and because gross output prices need not

correspond to final demand prices.

Another note on the equal weighting of industries: our objective in this short paper is to examine the relationship between AI and the economics at the industry level because estimating these relationships may be helpful in assessing the economic impacts of AI going forward as more AI adoption happens throughout the economy. This is different from trying to assess the macroeconomic impact of AI by weighting up industry impacts. In other words, if there is a small industry that is AI intensive in our dataset, we view the changes in that industry as potentially informative for the dynamics of AI, even if it is small sector.

Finally, differences in gross output price growth across industries are relatively easy to comprehend. Industries produce different outputs, and different outputs have different prices, so price growth differs by industry. But input price growth in our data can differ by industry as well, and this is a bit more difficult to understand. For primary inputs, like capital and labor, price differences are somewhat intuitive; the return to both factors of production and marginal productivities differ across industries, thus wage rates and capital service prices differ. For the intermediate inputs, the underlying assumption in the data assembly is that each industry pays the same price for each input in BEA's underlying use table. Therefore, differences in prices for intermediate inputs can vary by industry only if the composition (value share) of intermediates within each category (energy, materials, services) differs across industry. Therefore, one way to interpret our investigation is whether AI intensity was associated with a shift in the composition of intermediate inputs within each grouping leading to a difference in price growth within that category.

Initial regression results on the cost shares suggest a correlation that indicates that in terms of levels, AI intensity is not statistically significantly related to the distribution of costs (Table 2). But in terms of changes (first differences) of cost shares over time, AI intensity is associated with a shift away from labor and toward capital and materials (Table 3). This means that industries that were relatively intense in AI had labor shares that decreased in 2022 and 2023 more than non-AI-intensive industries. The model estimates that both the labor share paid to college and non-college workers experienced a decline that was related to AI. Cost shares sum to 1 by construction; therefore, the reduction in the labor share must be balanced by increases to other components of costs. The results indicate that costs allocated to capital and materials increased in AI-intensive industries. The model, however, is not able to parse the relative increase in capital share to the five components of capital that the ILPA tracks; i.e., the increase in the capital shares of IT equipment, software, R&D, entertainment originals, and other capital were all positive but not statistically significant.

Table 4 indicates that our AI intensity measure is related to costs and prices. Our baseline model estimates that AI intensity is associated with a relatively smaller contribution of labor and materials input prices to output price growth. To reiterate, this means that industries in the top quartile of AI

use had relatively lower labor and materials input price contributions to output price growth in 2022 and 2023 relative to the remainder of the industries. Relatively lower input price growth is consistent with the basic idea that AI is associated with downward pressure on wages and substitution away from workers toward other inputs (reflecting the interaction of supply and demand for workers within specific industries). The contribution variables that we include in the regressions are essentially the nominal value share times the price change of each input. Therefore, this result reflects the interaction of the two in determining the total price side contribution of each input. An extended example of what could be happening in determining this contribution: if AI reduces the demand for workers because AI can do tasks that workers used to do, this could lead to both less growth in wages in AI-intensive sectors relative to less AI-intensive sectors and a reduced share of workers relative to other inputs. Because many other changes have happened in the economy over this period, our approach is not able to pin down the many economic tradeoffs facing both workers and businesses with the introduction of AI but is intended to investigate atheoretically and empirically how the effects could be manifesting in the industry-level data. The intuition for the result that materials prices in AI-intensive industries contribute less than in non-AI-intensive industries is somewhat different. As mentioned above, an underlying assumption in the data is that purchasers pay the same price for each commodity at the level of detail at which BEA constructs its input-output accounts. Therefore, at that level of detail, AI intensity is uncorrelated with the price of materials input growth by construction. However, the aggregated price of materials paid by each industry is usually different because it reflects the composition of the bundle (i.e., each materials input nominal value share). Therefore, the result that AI intensity is correlated with a lower contribution of materials input prices captures two effects: (1) the composition of the bundle of materials within the material inputs (for example, substitution toward cheaper items within the bundle) and (2) substitution across the larger bundles of energy, services, capital, and labor. That is, a relatively lower contribution of materials prices could reflect less overall use of materials relative to the other broad input categories or the substitution toward cheaper materials inputs within the bundle materials. Both of these mechanisms are relevant for assessing the relationship between AI and costs and prices facing producers, thus the contribution variable is a useful summary variable.[3]

Furthermore, the model estimates that these same set of industries have output price growth that is slower in comparison to non-AI-intensive industries and that this slower price growth is statistically significant. For example, average price growth for each (unweighted) industry was a bit over 2% per year. The model results on gross output estimate that AI-intensive industries had lower price growth (relative to non-AI-intensive) by about 2% per year. While causal links remain outside the scope of this early research, these initial results are noteworthy because, if AI enables producers to bring down prices it charges for its goods or services, these reduced prices would make their way through the production chain, ultimately leading to lower prices for final purchasers. The relationship between AI, costs, and prices is consistent with predictions of a basic neoclassical model; in a competitive economy, reduced

[3] To disentangle these two would require data below the published level on the input-output tables. Because these data do not exist for the capital and labor inputs, the value of doing this is not clear.

costs (like those measured for labor and materials) are associated with reduced prices for purchasers. To be very clear, our results neither confirm this economic mechanism, nor causality. It could be the case that AI use is expensive and this (potentially unmeasured expense) requires the firms to temporarily (or perhaps permanently) underpay workers to compete with the promise of future hiring or wage increases. This may not be sustainable, and thus interpreting the results in a standard frictionless economic model may miss important dynamics and developments.

Like Highfill and Samuels [2026], we test an alternative specification to our baseline model. That paper discusses the choices that we need to make to implement our DiD model. In the alternative specification, instead of choosing 2022 to define AI intensity, we choose 2018. An interpretation of this definition is to focus on industries that were relatively early adopters. Table 5 shows that the results based on this alternative specification were broadly consistent for the price contribution variables with the baseline model that we discussed above. In particular, AI intensity is associated with lower output price growth by industry, and lower contributions of labor and materials prices relative to the remainder of industries. Because these are broadly consistent, we do not report regression results for the share variables, and leave additional specifications for future work.

5. Conclusions and Next Steps

A major motivation for this paper is to conduct early research on the relationship between AI and the macroeconomy using existing data. A previous paper, Highfill and Samuels [2026] focused on the real side of the economy, and this followup paper focuses on the cost and price side. We have found that AI intensity is associated with lower prices charged to purchasers, and some of this reduced price is related to restructuring input costs, in particular labor and materials costs.

Looking forward, it is crucial to develop measures of industry spending on AI and constant-quality price deflators for this spending. This would enable macroeconomic analysts and researchers to directly assess the relationship between AI and the sources of economic growth, instead of the indirect relationship that we have started to try to parse out in this paper.

Table 1: Summary Statistics Cost Structure and Prices

	Full sample mean	Non-AI pre-2022 mean	AI pre-2022 mean	Non-AI post-2021 mean	AI post-2021 mean
Capital share	0.1883	0.1679	0.2712	0.1950	0.2847
Labor share	0.3174	0.3095	0.3576	0.2985	0.3452
Entertainment originals share	0.0069	0.0007	0.0350	0.0006	0.0334
R&D share	0.0179	0.0159	0.0236	0.0251	0.0326
Information tech. equipment	0.0106	0.0065	0.0309	0.0035	0.0270
Other capital	0.1411	0.1367	0.1542	0.1554	0.1611
Software	0.0118	0.0081	0.0275	0.0103	0.0307
College labor	0.1470	0.1199	0.2639	0.1351	0.2805
Non-college labor	0.1704	0.1897	0.0938	0.1634	0.0646
Energy share	0.0326	0.0382	0.0098	0.0308	0.0076
Materials share	0.2102	0.2466	0.0489	0.2365	0.0415
Services share	0.2515	0.2379	0.3125	0.2391	0.3210
D Capital share	0.0020	0.0020	0.0018	0.0010	0.0093
D Labor share	-0.0011	-0.0012	-0.0012	0.0021	-0.0089
D Entertainment originals share	0.0001	0.0000	0.0002	0.0000	0.0024
D R&D share	0.0006	0.0005	0.0006	0.0008	0.0014
D Information tech. equipment	-0.0002	-0.0002	0.0000	-0.0001	0.0008
D Other capital	0.0012	0.0015	0.0003	0.0004	0.0031
D Software	0.0003	0.0002	0.0007	-0.0001	0.0016
D College labor	0.0011	0.0012	0.0018	-0.0008	-0.0081
D Non-college labor	-0.0022	-0.0025	-0.0030	0.0029	-0.0009
D Energy share	-0.0003	-0.0003	-0.0001	-0.0009	-0.0005
D Materials share	-0.0011	-0.0007	-0.0010	-0.0060	-0.0014
D Services share	0.0006	0.0003	0.0004	0.0038	0.0014
Dln Price Gross output	0.0226	0.0222	0.0120	0.0558	0.0228
Contribution K prices	0.0054	0.0049	0.0028	0.0145	0.0222
Contribution L prices	0.0097	0.0087	0.0107	0.0186	0.0094
Contribution PK entertainment orig.	0.0001	0.0001	0.0003	0.0000	0.0043
Contribution PK R&D	0.0006	0.0004	0.0008	0.0016	0.0020
Contribution PK IT equip.	-0.0008	-0.0005	-0.0022	0.0000	0.0000
Contribution PK other K	0.0056	0.0051	0.0040	0.0129	0.0157
Contribution PK software	-0.0001	-0.0001	0.0000	0.0000	0.0002
Contribution PL college	0.0047	0.0036	0.0085	0.0064	0.0071
Contribution PL non-college	0.0050	0.0051	0.0022	0.0123	0.0023
Contribution P energy	0.0013	0.0015	0.0003	0.0014	0.0003
Contribution P materials	0.0055	0.0064	0.0004	0.0100	0.0021
Contribution P services	0.0056	0.0055	0.0055	0.0070	0.0089
Observations	1647	1250	275	100	22

Notes. All shares are in nominal gross output at the industry level. D for the shares if first difference. D for ln is ln growth rate in prices.

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Table 2: Baseline Regression Results Shares Level

	Variable	Interaction term	SE	Constant	SE	R-squared
(1)	**Capital share**	-0.0136	(0.0155)	0.1885***	(0.0002)	0.8840
(2)	**Labor share**	-0.0015	(0.0094)	0.3174***	(0.0001)	0.9367
(3)	**Entertainment orig. share**	-0.0016	(0.0010)	0.0069***	(0.0000)	0.9576
(4)	**R&D share**	-0.0003	(0.0069)	0.0179***	(0.0001)	0.8572
(5)	**IT equipment share**	-0.0010	(0.0038)	0.0107***	(0.0001)	0.8794
(6)	**Other capital share**	-0.0118	(0.0118)	0.1412***	(0.0002)	0.9054
(7)	**Software share**	0.0010	(0.0019)	0.0118***	(0.0000)	0.8487
(8)	**College labor share**	0.0014	(0.0068)	0.1470***	(0.0001)	0.9672
(9)	**Non-college labor share**	-0.0029	(0.0062)	0.1704***	(0.0001)	0.9396
(10)	**Energy share**	0.0053*	(0.0027)	0.0325***	(0.0000)	0.8504
(11)	**Materials share**	0.0026	(0.0063)	0.2102***	(0.0001)	0.9808
(12)	**Services share**	0.0072	(0.0187)	0.2514***	(0.0003)	0.9213

n=1647

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 3: Baseline Regression Results Shares Change

	Variable	Interaction term	SE	Constant	SE	R-squared
(1)	**Capital share**	0.0084**	(0.0038)	0.0019***	(0.0004)	0.0348
(2)	**Labor share**	-0.0110***	(0.0036)	-0.0010*	(0.0005)	0.0799
(3)	**Entertainment orig. share**	0.0024	(0.0018)	0.0000	(0.0000)	0.0232
(4)	**R&D share**	0.0006	(0.0005)	0.0006**	(0.0003)	0.0329
(5)	**IT equipment share**	0.0009	(0.0009)	-0.0002*	(0.0001)	0.0188
(6)	**Other capital share**	0.0026	(0.0025)	0.0012**	(0.0004)	0.0342
(7)	**Software share**	0.0018	(0.0018)	0.0003**	(0.0001)	0.0245
(8)	**College labor share**	-0.0072**	(0.0029)	0.0012***	(0.0002)	0.0776
(9)	**Non-college labor share**	-0.0038***	(0.0011)	-0.0021***	(0.0004)	0.0806
(10)	**Energy share**	0.0004	(0.0007)	-0.0003**	(0.0001)	0.1459
(11)	**Materials share**	0.0046***	(0.0013)	-0.0012***	(0.0003)	0.1592
(12)	**Services share**	-0.0024	(0.0027)	0.0006	(0.0004)	0.0270

n=1586

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 4: Baseline Regression Results Prices Contributions

	Variable	Interaction term	SE	Constant	SE	R squared
(1)	**Gross output**	-0.0228***	(0.0058)	0.0229***	(0.0001)	0.2247
(2)	**Capital**	0.0098	(0.0065)	0.0053***	(0.0001)	0.0944
(3)	**Labor**	-0.0113**	(0.0040)	0.0098***	(0.0001)	0.1366
(4)	**Entertainment orig.**	0.0041	(0.0030)	0.0001**	(0.0000)	0.0394
(5)	**R&D**	-0.0001	(0.0008)	0.0006***	(0.0000)	0.0663
(6)	**IT equipment**	0.0016**	(0.0007)	-0.0008***	(0.0000)	0.2085
(7)	**Other capital**	0.0040	(0.0080)	0.0055***	(0.0001)	0.1085
(8)	**Software**	0.0002	(0.0001)	-0.0001***	(0.0000)	0.0183
(9)	**College labor**	-0.0042	(0.0030)	0.0047***	(0.0000)	0.1177
(10)	**Non-college labor**	-0.0071***	(0.0013)	0.0051***	(0.0000)	0.2041
(11)	**Energy**	-0.0000	(0.0005)	0.0013***	(0.0000)	0.2185
(12)	**Materials**	-0.0019**	(0.0009)	0.0056***	(0.0000)	0.2096
(13)	**Services**	0.0018	(0.0017)	0.0056***	(0.0000)	0.3604

n=1586

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 5: Alternative Specification Regression Results Prices Contributions

	Variable	Interaction term	SE	Constant	SE	R squared
(1)	**Gross output**	-0.0241***	(0.0045)	0.0231***	(0.0001)	0.2252
(2)	**Capital**	0.0050	(0.0065)	0.0053***	(0.0001)	0.0941
(3)	**Labor**	-0.0152***	(0.0034)	0.0099***	(0.0001)	0.1406
(4)	**Entertainment orig.**	0.0032	(0.0027)	0.0001*	(0.0000)	0.0382
(5)	**R&D**	-0.0004	(0.0008)	0.0006***	(0.0000)	0.0663
(6)	**IT equipment**	0.0019***	(0.0005)	-0.0008***	(0.0000)	0.2098
(7)	**Other capital**	-0.0001	(0.0068)	0.0056***	(0.0001)	0.1084
(8)	**Software**	0.0004**	(0.0002)	-0.0001***	(0.0000)	0.0183
(9)	**College labor**	-0.0071**	(0.0027)	0.0048***	(0.0000)	0.1201
(10)	**Non-college labor**	-0.0081***	(0.0011)	0.0052***	(0.0000)	0.2071
(11)	**Energy**	0.0000	(0.0005)	0.0013***	(0.0000)	0.2185
(12)	**Materials**	-0.0025**	(0.0010)	0.0056***	(0.0000)	0.2097
(13)	**Services**	-0.0027	(0.0031)	0.0057***	(0.0001)	0.3613

n=1586

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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