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## Comparing early estimates of US manufacturing output

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Working Paper 592  
September 2026

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## Abstract

Measures of labor productivity can be based on different concepts of output. This paper examines measures of quarterly output for the U.S. manufacturing sector. Gross output is the value of goods produced in manufacturing establishments. Sectoral output subtracts the costs of intermediate inputs (energy, materials, and services) purchased from within that sector, which reduces the double-counting of goods both produced and used in the sector. Value-added output subtracts the costs of all intermediate inputs and is the measure of output used in GDP. This paper compares sectoral and value-added output growth over time and discusses the justifications for using each concept in measures of productivity. It explores simple prediction models of components of these output measures using data available within one month of the end of each quarter. In both durable and nondurable goods manufacturing, sectoral output tends to grow faster than value added in periods when import prices are rising. In durables manufacturing, increases in new orders, temporary help employment, and overall manufacturing employment help predict when sectoral output grows faster than value added. This paper explains these relationships and examines differences in growth rates to help readers interpret productivity statistics based on these different output concepts.

JEL Classification: E01, L6, O4

Keywords: Output measurement; manufacturing; prediction; productivity; national accounts

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<sup>1</sup> Views expressed in this paper are those of the author and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics. The author thanks many experts for their advice and data: Jose Asturias, David Byrne, Barbara Fraumeni, John Glaser, Jennifer Kim, Tom Kovarik, Andrew Martinez, Sabrina Pabilonia, Matt Russell, Jon Samuels, Rachel Soloveichik, Shawn Sprague, Jay Stewart, Leo Sveikauskas, Maria Tito, Cliff Waldman, and T. Kirk White.

# Introduction

Measure of labor productivity published by the Bureau of Labor Statistics (BLS) compare economic output to labor hours worked. The different measures of labor productivity use different measures of output, either value-added or sectoral output. This article explains why each concept is used, examines what circumstances cause the measures to move at different rates, and examines how to use data available shortly after each quarter to estimate how much each output measure grew.

Productivity research often devotes substantial attention to the measurement of inputs, while treating output measures as given. However, the choice of output concept can affect productivity estimates substantially. This paper focuses on output measures for durable and nondurable goods manufacturing industries, drawing on official quarterly data produced by multiple statistical agencies and ultimately based mainly on Census Bureau data and BLS price indexes.

The next section examines conceptual differences between sectoral output and value added, and the purposes for which each is best suited. In one key example, in a period in which computer manufacturing increasingly moved offshore, the two series grew at different rates, providing two pictures of productivity growth in that period. A subsequent section shows how to predict value-added and sectoral output within a month of the end of each quarter, so data users can quickly understand differences in the movements of these two series and the resulting productivity statistics.

## Three output measures for US manufacturing sectors

BLS publishes quarterly measures of productivity growth based on two alternative measures of output: value-added and sectoral output. These are standard concepts, each based on an underlying third measure, gross output. This section explains what the differences are, and why BLS uses these two different measures.

The main difference between the measures discussed here is how they adjust for the costs of intermediate inputs used in production. Charts 1 and 2 show the main data, measured in nominal (current-dollar) terms. Durable goods manufacturing refers to industries producing goods generally lasting three years or more, such as cars, furniture, and drill presses. Nondurable goods manufacturing covers all other U.S. manufacturing establishments, such as those making food, plastics, and chemicals. When this paper refers to sectors, it means these two industry groups.

The top line in each chart is **gross output**. It is defined as the value produced by the manufacturing establishments -- their product sales, plus their net change in inventories, plus

their creation of their own capital assets through investment into R&D, software, or entertainment originals. Gross output is the basis for the other output measures. All the output measures discussed here are seasonally adjusted, so the charts do not reflect recurring seasonal patterns.

**Chart 1: Quarterly durable goods manufacturing output measures, 2005-2022**

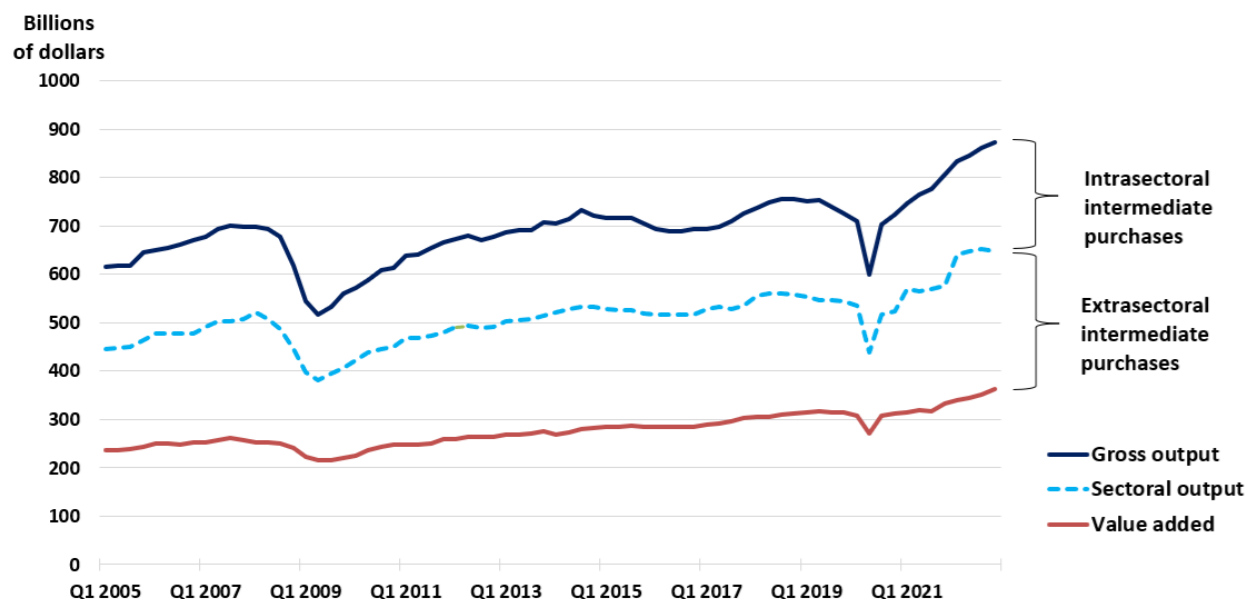
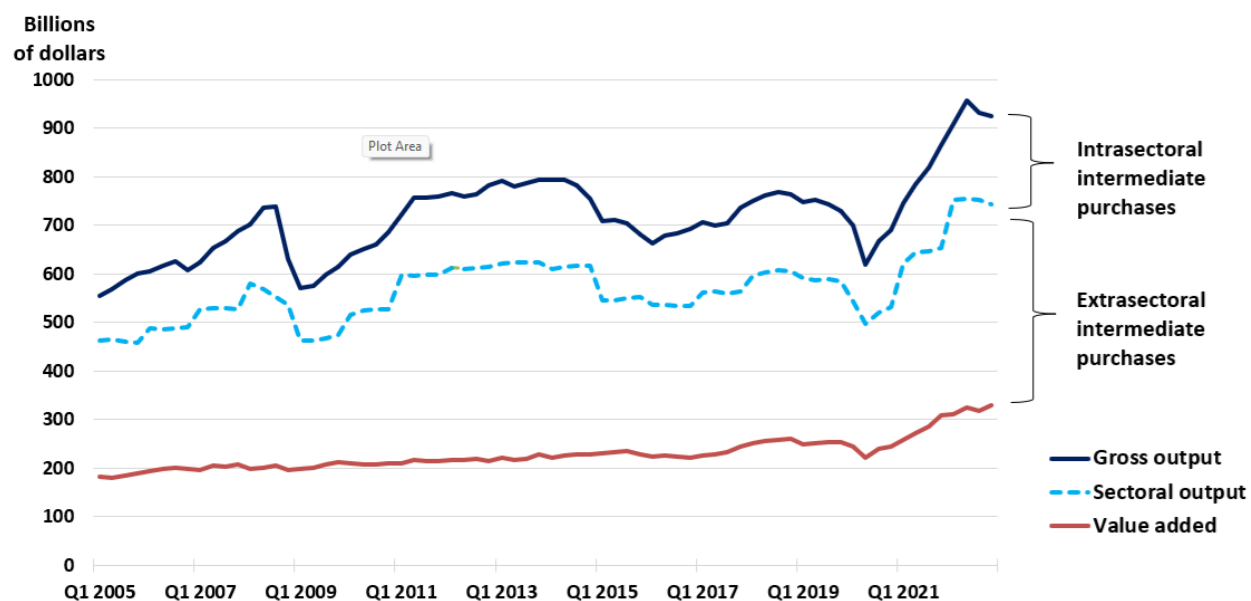


**Chart 2: Quarterly nondurable goods manufacturing output measures, 2005-2022**



**Sectoral output** for these manufacturing sectors is computed by starting with gross output and subtracting the cost of intermediate inputs that their establishments purchase from other

establishments in the same domestic sector. Intermediates generally include purchased materials, and often include purchases of energy and services. This adjustment is intended to remove the output that the establishments in a sector deliver to one another, in order to measure the net value that the sector delivers to other industries. The middle lines on Charts 1 and 2 show estimates of nominal sectoral output, constructed using the procedure described in Appendix A.

An example helps clarify why sectoral output could be a useful output measure. If two manufacturing establishments in the same sector sell intermediate parts to one another, these transactions are all included in gross output. If these establishments were to merge, with no other change, gross output would decline because these intermediate transactions would no longer be external market transactions but rather would be shipments of goods within an establishment. Thus, gross output can fluctuate when there is a change in vertical integration, whereas sectoral and value-added measures are not affected by such mergers or divestments. If all establishments in a sector merged into one, the sector's gross output would fall to the level of sectoral output.

The benefit of sectoral output over gross output is that it avoids counting the revenue generated from sales between establishments within the sector and then double counted when the same output incorporated into a finished product is sold outside the sector. Sectoral output is a measure of the amount that a sector produces that is sold to other sectors (usually wholesalers), sold to the public, added to a firm's own capital stock, or exported. A tricky issue is that the scope of a sector affects the definition and size of intrasectoral transactions. For instance, when constructing sectoral output measures for both a narrow 4-digit NAICS industry category and the broader 3-digit category that includes it, the 4-digit sectoral outputs do not sum up to 3-digit sectoral output. Sales between establishments in different 4-digit categories within the same 3-digit NAICS category are intrasectoral transactions for the larger industry.

**Value-added output** is computed by subtracting the value of all intermediate purchases, from any industry or country of origin, from gross output. Intermediates include purchased materials, energy, and services that are not capitalized by national accountants. Value added is illustrated by the lowest line on the charts. GDP is a value-added measure: the sum of value-added output for all the industries in an economy, both private and public. In productivity measures, value-added output is modeled as the value that the industry adds to the economy through its use of productive capital and labor.

The difference between value-added output and sectoral output measures is the value of intermediate inputs that US manufacturing establishments purchase from outside that sector – that is, from other industries or imports. This paper calls these “extrasectoral intermediates.” Other studies use the equivalent phrase “intersectoral transactions and imports.”

## Output measures in productivity analysis

Several practical differences among these output measures affect productivity calculations. First, these output measures differ substantially in levels. In overall US manufacturing, sectoral output is approximately 70 percent of gross output, while value added is roughly 40 percent of gross output. These proportions change systematically for subsets of manufacturing as the magnitude of intrasectoral transactions shrinks in more detailed categories. For the smallest industry categories, there are no intrasectoral transactions, so sectoral output and gross output converge.

Another difference is that these output measures sum differently across sectors. For gross output and value-added output, the total for U.S. manufacturing is the sum of the durable and nondurable sectors. However, for sectoral output, the definition of “intrasectoral transactions” is different for overall manufacturing than for the subsectors, because intermediate inputs such as oil or rubber are sold between the durable and nondurable sectors.

A third difference concerns the timing of when the measures are published and available. The Bureau of Economic Analysis (BEA) publishes gross output and value-added output approximately 35 days after the end of each quarter. Constructing sectoral output estimates requires detailed data that distinguishes between different kinds of intermediate inputs and their sources by industry or country (Kovarik and Varghese, 2019). The BEA publishes such data for Economic Census years. BLS prepares quarterly estimates of intrasectoral transactions based largely on the Industrial Production Indexes that the Federal Reserve publishes each month. BLS publishes manufacturing productivity statistics each quarter based on estimates of real sectoral output. (For details, see Appendix A.)

Movements in these output series are highly correlated. A later section considers how the effects of outsourcing and imports affect these output measures.

Value-added output is the most-used measure of output. It is appropriate for economy-wide productivity measures and for productivity measures that can be combined or weighted to determine the contributions of each industry to national productivity. Value added is a standard concept used in international comparisons of productivity such as those published by the UN, ILO, and OECD.

However, to understand movements in industry productivity, it can be more informative to use sectoral or gross output to incorporate more industry choices among the full complement of inputs (factors of production). This is appropriate for total factor productivity (TFP) models, which incorporate more information about inputs than labor productivity does. Gollop (1979) developed sectoral output measures for this purpose. When measuring productivity and

including both labor and capital inputs, estimates of the effects of labor and capital inputs can be biased when using a value-added measure of output that simply subtracts out the costs of some intermediate inputs. Productivity models typically assume firms maximize revenue minus costs, not revenue minus costs excluding intermediates.

A scholarly literature addresses the use of gross, sectoral, or value-added measures of output to estimate the contributions and shares of labor and capital. Studies find that for many industries, the use of value-added output in multifactor (total factor) productivity measures introduces substantial biases.<sup>2</sup> Therefore, for TFP estimates, most analysts use gross output or sectoral output rather than value added.

This bias does not affect estimates of labor productivity used in this paper. However, in comparing labor productivity to TFP within an industry, it can be desirable to use the same output concept to get a direct sense of the contribution of capital to labor productivity. Gullickson and Harper (1995, 1999) argue therefore that it is appropriate to use sectoral output for quarterly manufacturing labor productivity.

Three example cases illustrate patterns that cause sectoral and value-added output measures to grow differently.

### **Case 1: Offshoring of computer and electronics manufacturing**

The U.S. computer industry grew quickly from 1997 to 2021, as the proportion of Americans owning some kind of computer rose from approximately 35% to 95% over this period.<sup>3</sup> For the computers and electronic industry (NAICS 334), sectoral output doubled in this period whereas value-added output grew by a factor of seven. Eldridge and Powers (2023a, 2023b) examined this difference. In this period, production and assembly of computers increasingly shifted overseas, so less U.S. labor was used for manufacturing products, and domestic establishments bought fewer intermediate goods from U.S. suppliers. Eldridge and Powers found that the measured intermediates value declined approximately 5% a year even as the industry grew in sales and gross output terms. U.S. firms continued to perform substantial design, research and

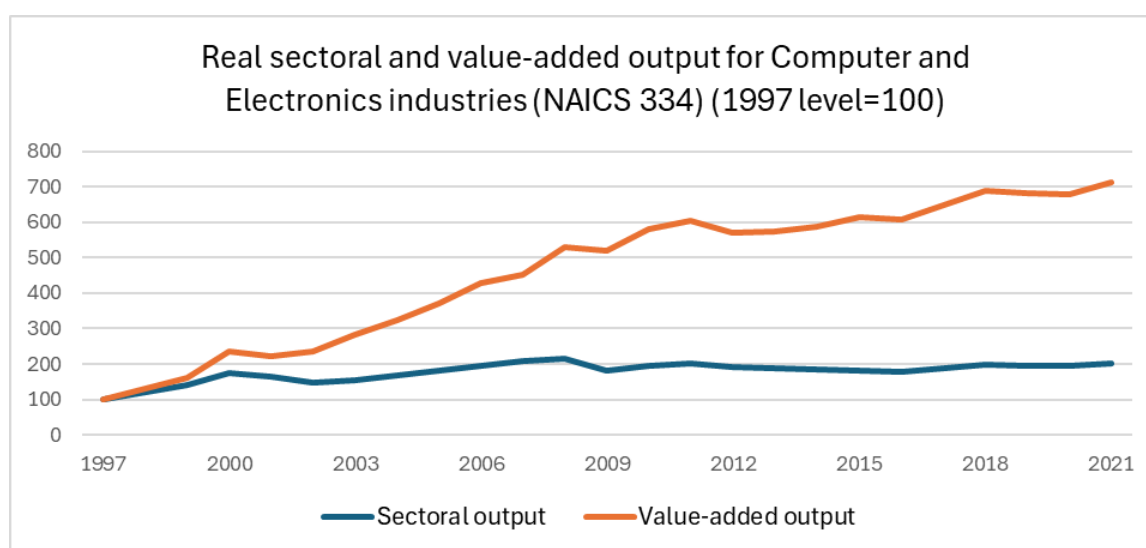
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<sup>2</sup> The issue is characterized as one of “the existence of a value-added function,” and of whether the intermediates are “separable” in the production function. If the empirically appropriate production function has a form in which the intermediates are “separable” from labor and capital, then value-added output can be used without causing a significant bias. As an example of when it would matter, consider that if a manufacturing firm imports particularly high-quality materials, then it may not need to use as much labor in the US. Then the choices about imports – extrasectoral purchases and their costs – directly affect the use of “primary inputs” labor and capital. Sophisticated empirical studies have found that the assumption of separability is not empirically supported, and that therefore value-added output did not meet the productivity model assumptions. (Berndt and Wood, 1975; Jorgenson, Gollop, and Fraumeni, 1987, pp 258-260). Gandhi, Navarro, and Rivers (2017) reexamined the issues and surveys a more recent literature.

<sup>3</sup> These figures on computer ownership come from <https://www.bls.gov/opub/ted/1999/Apr/wk1/art01.htm> and <https://www.census.gov/newsroom/press-releases/2024/computer-internet-use-2021.html>.

development, marketing, and managerial functions, and earned growing revenues and profits. As gross output grew while intermediate expenditures declined, value-added grew much more rapidly than sectoral output. Chart 4 shows how the two output measures grew over this the period. (The chart shows relative growth since 1997, not levels; in levels, value added is never above sectoral output.)

**Chart 3. Output measures for Computer and Electronics Manufacturing, 1997-2021**



Data source: Eldridge and Powers (2023a,b)

The difference in this case is extreme, caused by several trends: rapid growth of the industry in terms of overall sales, sharp declines in prices of components, and sharp reductions in flows of intermediates as offshoring of production occurred. These movements have an effect on labor productivity measures in this sector, causing value added per hour worked in the U.S. to grow quickly. In principle, a “factoryless” goods producer might have growing sales but almost no intermediate purchases in the U.S.; its output would be attributed to its capital and labor, while any physical intermediate transactions would be in other countries or other industry sectors, so its value-added growth would exceed its sectoral output growth. The empirical work below shows that variations in import prices and volumes strongly predict the difference between value-added and sectoral output for manufacturing.

## Case 2: Outsourcing to temporary help services

Employers may reassign work from internal staff to outside contractors. Janitorial services is a common case. This change reduces measured labor input, and replaces that by a purchased service, an intermediate input purchased from other industries. Susan Houseman and colleagues have examined this topic extensively. They find that employment services are important in

manufacturing and lead to meaningfully different estimates of productivity depending on how they are prepared (Houseman, 2006; Houseman, Kurz, Lengermann, and Mandel 2011; Dey, Houseman, and Polivka, 2012 and 2017). A switch to outsourcing affects the difference between value-added and sectoral output. The next sections shows that quarterly fluctuations in temporary employment are correlated with such differences for durables, but less so for nondurables. Houseman et al. find other issues in methods and assumptions in the estimates of employment services, which are not addressed here.

### **Case 3: Leased capital services**

Software is increasingly licensed rather than purchased, which means that instead of a capital investment occurring at one moment as a purchase, it is a series of service payments. Where possible, BEA identifies these as capital investments (Highfill, Wasshausen, and Prunchak, 2025). The same issue arises for purchases of cloud computing and some AI services; if a company transfers its databases to a provider of GenAI services that trains an LLM on them and can then answer questions or make synthetic statements, the company is investing in capital stock even if it pays in the form of a service fee. In such an arrangement, which might be called “capital outsourcing,” some capital investments would be measured as extrasectoral intermediate services, and if this occurs, expenditures on them would be included in sectoral output but not value-added. Tebrake and Strassner (2026, p. 18) note this difficulty in measuring the effects of Gen AI in productivity measures: “Generative AI is increasingly consumed as a service--through per-query API charges, subscription licenses, and cloud-based access--rather than acquired as an own-account capital asset.” The empirical work below does not test for this issue, e.g., whether use of AI services causes a significant divergence among the output measures.

## **Six components of manufacturing gross output**

This section develops measures of six components of quarterly output. It examines patterns of their that can be detected early after the quarter is over. I divide each quarter’s nominal gross output for the manufacturing sector into six components. I estimated current-dollar sectoral output for each quarter, which makes it possible to divide intermediate expenditures into intrasectoral and extrasectoral subsets. The series for this study cover 71 quarters, from 2005Q2 to 2022Q4, as determined by data availability. See Appendix A for further details on the data sources and construction.

These six components add up to the output measures shown in Charts 1 and 2, for durables and nondurables separately:

Sectoral output = Value-added + Extrasectorals

Gross output = Value-added + Extrasectorals + Intrasectorals

That is, sectoral output is made up of value added plus the value of intermediates purchases from outside the sector, and gross output includes all intermediates. Splitting output into these six components brings some insights. Better precision could be achieved by predicting all three components separately for each of the 21 three-digit NAICS manufacturing industries, but that is beyond the scope of this work.

These calculations are in nominal terms so that the components add up exactly. Real (constant dollar) growth would be of interest but it would require more data and more assumptions. On average, inflation was 2.4% per year over this period, by either CPI or PPI, so real growth was probably negative for all the elements shown.

The six components of gross output all grow in nominal terms, as Table 1 shows. Prices rose faster for nondurables in this period, which is why their nominal output growth was faster.<sup>4</sup>

**Table 1. Growth rates of nominal output measures and components, 2005Q2-2022Q4**

| Output measure or component | Compounded annual average growth | Std dev of annual average growth |
|-----------------------------|----------------------------------|----------------------------------|
| Durable value added         | 0.60%                            | 2.93%                            |
| Durable sectoral output     | 0.53%                            | 4.14%                            |
| Durable gross output        | 0.49%                            | 3.80%                            |
| Durable intermediates       | 0.42%                            | 4.66%                            |
| Durable extrasectorals      | 0.44%                            | 6.79%                            |
| Durable intrasectorals      | 0.40%                            | 6.00%                            |
| Nondurable value added      | 0.84%                            | 2.83%                            |
| Nondurable sectoral output  | 0.67%                            | 4.67%                            |
| Nondurable gross output     | 0.72%                            | 3.87%                            |
| Nondurable intermediates    | 0.66%                            | 4.85%                            |
| Nondurable extrasectorals   | 0.54%                            | 7.73%                            |
| Nondurable intrasectorals   | 0.98%                            | 15.51%                           |

The standard deviations in Table 1 show that value-added measures are less volatile from quarter to quarter than sectoral or gross output ones. This is associated with the contributions of capital, which take time to acquire and develop and then depreciate slowly; employers don't adjust their equipment and structures as quickly as they can adjust labor and intermediate

<sup>4</sup> PPIs are usually the appropriate indexes for this data, but CPIs illustrate the point plainly: overall CPI-U growth rates for durables were only 0.6% per year on average in this period, but were 2.4% on average for nondurables.

inputs.<sup>5</sup>

Table 2 shows pairwise correlations in the quarterly movements of these growth rates. The correlations in the upper right are positive because more economic activity is correlated to more activity in related sectors. The strong correlation of extrasectoral activity across the sectors is due to fluctuations in imports being correlated across the two sectors. The lower or negative correlations between nondurable extra- and intrasectorals occur because manufacturers can substitute across these sources of intermediates.

**Table 2. Correlations of quarterly growth in nominal output components, 2005Q2-2022Q4**

|                                 | <b>Durable<br/>VA</b> | <b>Nondurable<br/>VA</b> | <b>Durable<br/>extrasectoral<br/>intermediates</b> | <b>Nondurable<br/>extrasectoral<br/>intermediates</b> | <b>Durable<br/>intrasectoral<br/>intermediates</b> |
|---------------------------------|-----------------------|--------------------------|----------------------------------------------------|-------------------------------------------------------|----------------------------------------------------|
| <b>Durable VA</b>               |                       |                          |                                                    |                                                       |                                                    |
| <b>Nondurable VA</b>            | 0.544                 |                          |                                                    |                                                       |                                                    |
| <b>Durable extrasectoral</b>    | 0.599                 | 0.402                    |                                                    |                                                       |                                                    |
| <b>Nondurable extrasectoral</b> | 0.242                 | 0.005                    | 0.710                                              |                                                       |                                                    |
| <b>Durable intrasectoral</b>    | 0.609                 | 0.414                    | 0.449                                              | -0.199                                                |                                                    |
| <b>Nondurable intrasectoral</b> | 0.226                 | 0.531                    | -0.053                                             | -0.531                                                | 0.489                                              |

## Early estimates of the output components

The empirical analysis below covers 71 quarters from 2005Q2 through 2022Q4, using seasonally adjusted growth rates on nominal data (that is, in current dollars). The regressions to be shown use data available early after each quarter to predict the six components of economic activity that add up to manufacturing gross output, for the durable goods and nondurable goods sectors separately. The predictor variables used are available within a month of the end of the quarter, before the first GDP release, and the dependent variables used are the most recent estimate of the output component, not the value first published in the first GDP release.

I have explored many predictors for making early estimates, from the Census Index of Economic Activity (IDEA) program, data on temporary help services, CPIs, PPIs, and other standard statistics. Appendix A provides data details. Employment services industry growth (NAICS 5613) was highly correlated ( $p=0.886$ ) to manufacturing employment growth overall and I chose the one predicting best in context.

The predictors are selected to help make inferences about the hypotheses that will help

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<sup>5</sup> In an extreme case, the COVID-19 shock, monthly flows of manufacturing labor and intermediates input declined about 20% in a single month. In more normal times, adjustment of labor inputs is much slower. Except for recession and emergency periods, employers adjust labor hours slowly, a pattern labor economists call “labor hoarding.” Changing intermediates often requires altering contracts, evaluating quality, and managing lead times.

explain differences in output movements, not to make the most accurate prediction. More accurate predictions could be made from the nowcasting indexes that predict manufacturing GDP movements, such as the Federal Reserve's Industrial Production Indexes, the Atlanta Fed's GDPNow, or the Weekly Economic Index. Because these are complex combinations of other data, they would not necessarily provide clear intuition about the forces in play. More accurate predictions could also be made by waiting longer; the variables used here are available within 30 days of the quarter's end.

All these variables have been transformed to quarter-to-quarter growth rates. Money values are in nominal (current) dollars. Price indexes are included in the linear regressions. Seasonally adjusted data is used wherever possible to avoid quarterly seasonal effects. I choose predictors to have some empirical traction, some intuitive meaning, and to avoid collinearity and structural breaks as according to the tests described in Appendix B.

Table 3 shows regressions with predictions of value-added output growth.

**Table 3: Predictors of quarterly growth of value-added output in the same quarter**

| Predictors                   | (1)<br>Durable goods<br>manufacturing | (2)<br>Nondurable goods<br>manufacturing |
|------------------------------|---------------------------------------|------------------------------------------|
| Manufacturing employment     | 0.832***<br>(0.150)                   | 0.224<br>(0.220)                         |
| Total exports                | 0.255***<br>(0.057)                   |                                          |
| New orders for durable goods | 0.067<br>(0.040)                      |                                          |
| Business applications        | 0.086***<br>(0.017)                   |                                          |
| Import price index           | -0.245***<br>(0.068)                  |                                          |
| New orders for nondurables   |                                       | 0.316***<br>(0.119)                      |
| CPI durables growth          |                                       | 0.520***<br>(0.183)                      |
| CPI nondurables growth       |                                       | 0.487**<br>(0.188)                       |
| PPI of manufacturing output  |                                       | -0.422***<br>(0.158)                     |
| Constant                     | 0.004**<br>(0.002)                    | 0.006**<br>(0.003)                       |
| Observations                 | 71                                    | 71                                       |
| Adjusted $R^2$               | 0.840                                 | 0.495                                    |

Notes: Predictors and dependent variables are growth rates relative to the previous quarter. All variables are from the same reference quarter. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, 10% level.

The patterns differ between durables and nondurables. For durables, increases in manufacturing employment and exports are associated with more production and value added. When import prices decline, value added in the quarter tends to increase, presumably because the costs of production have declined. When new business applications rise, output also rises; presumably here the effects go in both directions – the new business generates output itself, and high output is associated with new niche opportunities for a new business to be created. The overall accuracy of the prediction of durable goods value-added output is high; this regression predicts 84% of the variation of value-added growth for durables.

For nondurables, consumer price indexes are statistically significantly positively correlated to value-added output growth, and PPIs negatively correlated. Intuitively this might be because high output prices are associated with more production, and high input prices with lower production, but no further test for causality has been applied. Including all these variables, the predictive accuracy of the nondurables regression is much lower than that of durables; it explains only half of the variation. Other studies also find that durables manufacturing activity is more accurately predicted than nondurables (e.g. Meyer and Martinez, 2017).

Table 4 reports regressions that analyze the value of intermediates for the two sectors, the sum of intrasectorals and extrasectorals. Purchases of intermediate inputs increase in quarters where new orders, imports, and temporary employment increase. For nondurables, intermediate purchases increase when imports and new orders rise, but fluctuations in temporary employment have a small effect and an unexpected negative sign. Of these regressions, columns (2) and (3) are the most stable for forecasting.<sup>6</sup>

**Table 4: Predictors of quarterly growth of intermediates by manufacturing sector**

|                                              | (1)<br>Durable goods | (2)<br>Durable goods | (3)<br>Nondurable<br>goods | (4)<br>Nondurable<br>goods |
|----------------------------------------------|----------------------|----------------------|----------------------------|----------------------------|
| New orders for durable goods                 | 0.352***<br>(0.049)  | 0.289***<br>(0.049)  |                            |                            |
| Total imports                                | 0.554***<br>(0.061)  | 0.446***<br>(0.064)  | 0.288***<br>(0.069)        | 0.405***<br>(0.087)        |
| Employees in employment<br>services industry |                      | 0.231***<br>(0.065)  |                            | -0.127**<br>(0.061)        |
| New orders for nondurables                   |                      |                      | 0.867***<br>(0.082)        | 0.834***<br>(0.082)        |
| Constant                                     | -0.004*<br>(0.002)   | -0.002<br>(0.002)    | -0.002<br>(0.002)          | -0.003*<br>(0.002)         |
| Observations                                 | 71                   | 71                   | 71                         | 71                         |
| Adjusted $R^2$                               | 0.899                | 0.914                | 0.918                      | 0.922                      |

Notes: Predictors and dependent variables are growth rates relative to the previous quarter. All variables are from the same reference quarter. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, 10% level. Data sources are discussed in the text

Sectoral output includes some of the intermediate purchases. Tables 5-7 show influences on the two categories of intermediates, the “intrasectorals” purchased from within the same sector (say, US durables manufacturing) and the “extrasectorals” imported or purchased from other sectors. These regressions have less predictive power than the ones for total intermediates shown in Table 4.

Table 5 presents regression results that predict extrasectoral intermediate purchases by the durable goods sector. Extrasectoral intermediates are the difference between sectoral and value-added measures, and are shown as the distance between the two lower lines on Charts 1 and 2.

The first regression shows that import prices and volumes predict more than 60% of the variation in this difference for durables. A quarter-to-quarter increase in import prices and

<sup>6</sup> The regressions have high accuracy and statistical significance, but a Chow test finds a structural break within this period in 2013- 2014 in the estimates for nondurables. In the earlier period, new orders for nondurables and imports have much higher coefficients than in the later period. It is not clear why. The shift away from the significance of imports could be associated with the shift from imported fuels toward domestically produced oil and gas.

volumes is associated with sectoral output rising faster than value added. The overall proportion of imports in intermediates has been estimated at about 30%, so it would be about twice that high in the extrasectorals alone. The import variables here, from the Census IDEA data set, cover imports overall and do not focus on intermediates; data making that distinction become available later.

**Table 5. Predictors of extrasectoral intermediates in durable goods manufacturing**

|                                           | (1)                 | (2)                 | (3)                  | (4)                  |
|-------------------------------------------|---------------------|---------------------|----------------------|----------------------|
| Total imports                             | 0.925***<br>(0.125) |                     | 0.460**<br>(0.174)   | 0.361**<br>(0.167)   |
| Import price index                        | 0.636***<br>(0.235) | 1.088***<br>(0.180) | 1.853***<br>(0.284)  | 1.897***<br>(0.269)  |
| Manufacturing employment                  |                     | 1.495***<br>(0.387) | 1.032***<br>(0.384)  |                      |
| New orders for durable goods              |                     | 0.380***<br>(0.109) | 0.317***<br>(0.113)  | 0.236**<br>(0.111)   |
| Business applications                     |                     | 0.116**<br>(0.053)  | 0.145***<br>(0.047)  | 0.141***<br>(0.044)  |
| PPI of combined energy inputs             |                     |                     | -0.349***<br>(0.099) | -0.363***<br>(0.092) |
| CPI durables growth                       |                     |                     | -1.204***<br>(0.291) | -1.273***<br>(0.276) |
| Employees in employment services industry |                     |                     |                      | 0.556***<br>(0.143)  |
| Constant                                  | -0.007<br>(0.005)   | -0.001<br>(0.004)   | -0.005<br>(0.004)    | -0.006<br>(0.004)    |
| Observations                              | 71                  | 71                  | 71                   | 71                   |
| Adjusted $R^2$                            | 0.628               | 0.722               | 0.795                | 0.816                |

Notes: Predictors and dependent variables are growth rates relative to the previous quarter. All variables are from the same reference quarter. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, 10% level.

The second regression shows that changes in overall manufacturing employment and new orders are also positively correlated with changes in extrasectoral intermediate purchases in the same quarter. The associations with employment and new orders are stronger than they are for value added (shown in Table 3), so these variables characterizing activity are also correlated with differences in growth between value-added and sectoral output measures.

The third regression includes two additional price variables. An upward jump in producer or consumer prices is associated with statistically significantly reduced expenditures on extrasectoral intermediates. There are several forces in play here, because a rise in prices implies that the manufacturers pay higher input costs and receive higher prices for their output. A more comprehensive model could incorporate supply and demand effects separately.

The fourth regression shows the relevance of the employment services industry in particular. Most of the employment in this industry (NAICS 5613) is made up of temporary help employees; others include the long-term employees of staffing services, executive search agencies, and professional services contractors. Fluctuations in this category are statistically significant predictors of extrasectoral intermediate expenditures and the regression accuracy improves relative to the one that uses changes in manufacturing employment overall. This is consistent with the line of thought in Houseman (2006) and related literature that productivity measures are substantially affected by variations in domestic outsourcing.

Table 6 shows a similar set of regressions results for extrasectoral purchases of intermediates by nondurable goods manufacturers. Different variables predict durable and nondurable activity.

**Table 6. Predictors of extrasectoral intermediates in nondurable goods manufacturing**

|                                                            | (1)                 | (2)                 | (3)                  | (4)                  |
|------------------------------------------------------------|---------------------|---------------------|----------------------|----------------------|
| Import price index                                         | 1.221***<br>(0.361) | 2.566***<br>(0.523) | 2.888***<br>(0.556)  | 1.691***<br>(0.477)  |
| Total imports                                              | 0.431**<br>(0.192)  | 0.654***<br>(0.191) | 0.691***<br>(0.190)  | 0.663**<br>(0.319)   |
| PPI of combined energy inputs                              |                     | -0.611**<br>(0.182) | -0.702***<br>(0.200) |                      |
| Hours worked, temporary<br>employment services             |                     |                     | 4.933**<br>(1.895)   |                      |
| Weekly hours of employees of<br>professional employer orgs |                     |                     | -5.191***<br>(1.886) |                      |
| New orders for nondurables                                 |                     |                     |                      | -0.910*<br>(0.499)   |
| PPI of manufacturing output                                |                     |                     |                      | 1.372***<br>(0.467)  |
| CPI durables growth                                        |                     |                     |                      | -1.403***<br>(0.487) |
| CPI nondurables growth                                     |                     |                     |                      | -1.901***<br>(0.515) |
| Manufacturing inventories                                  |                     |                     |                      | 1.435**<br>(0.547)   |
| New homes sold                                             |                     |                     |                      | -0.190**<br>(0.089)  |
| Construction spending                                      |                     |                     |                      | -0.664**<br>(0.286)  |
| Construction units started                                 |                     |                     |                      | 0.386***<br>(0.118)  |
| Constant                                                   | -0.003<br>(0.008)   | -0.005<br>(0.007)   | -0.005<br>(0.007)    | -0.007<br>(0.008)    |
| Observations                                               | 71                  | 71                  | 66                   | 71                   |
| Adjusted $R^2$                                             | 0.324               | 0.413               | 0.472                | 0.545                |

Notes: Variables are growth rates relative to the previous quarter. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, 10% level.

The first column of Table 6 show that changes in imports and their prices are positively associated with extrasectoral purchases here, but less strongly than for durables. The second column shows that increases in the price of energy inputs are negatively associated with growth in purchases of these intermediates overall. The third regression includes strong predictors that are harder to explain, which shows that higher accuracy of prediction is probably possible using data available before the output measures are published with a more sophisticated model. Measures of temporary employment are sometimes able to improve prediction accuracy, but not in a consistent and understandable way.

A combination of housing construction variables predict extrasectorals for nondurables. The pattern suggests that when the builders and the buyers make purchases in the same quarter as the home sale occurs, e.g. of paint, detergent, and food, the effect is strong enough to help predict manufacturing activity. This observation is associated with the literature following Leamer (2007) that housing-related economic activity is the main core of the business cycle itself. In the context here, the relevant finding is that movements in housing activity drive statistically differences between value-added and sectoral output measures for nondurables, but the variables available did not give a reliable predictive structure to this effect.

Import prices are highly correlated with extrasectoral purchases for both durable goods and nondurable goods, according to Tables 5 and 6. The main pattern seems to be simply that when import prices are relatively high, these industries pay more for them, and do not quickly switch to domestic suppliers. (Import price movements predict about 34% of quarterly variation in the imports.) However, these purchases are often part of long-term contracts, with prices fixed in advance. An offshoring pattern, for example, involves a long-term commitment, and manufacturers cannot realistically switch suppliers because of price fluctuations. The regressions shown do not distinguish among these effects.

Table 7 fills out the output components picture with regression results on intrasectoral intermediates. If their growth were highly predictable, it could be possible to estimate extrasectorals by (intermediates minus intrasectorals) but in this sample the regressions are not accurate or robust enough to produce good estimates.

**Table 7. Intrasectoral purchases of intermediate inputs by manufacturing sector**

| Predictor                                             | (1)<br>Durable goods | (2)<br>Nondurable<br>goods | (3)<br>Nondurable<br>goods |
|-------------------------------------------------------|----------------------|----------------------------|----------------------------|
| Import price index                                    | -1.743***<br>(0.299) | -3.028***<br>(1.047)       | -3.047***<br>(0.950)       |
| New orders for durable goods                          | 0.467***<br>(0.093)  |                            |                            |
| PPI for final demand,<br>excluding energy commodities | -3.379**<br>(1.299)  |                            |                            |
| CPI durables growth                                   | 1.711***<br>(0.379)  |                            |                            |
| CPI nondurables growth                                | 0.825**<br>(0.314)   |                            |                            |
| Wholesale inventories                                 | 1.312***<br>(0.333)  |                            |                            |
| Export price index                                    |                      | 1.590*<br>(0.836)          | 1.959***<br>(0.705)        |
| New orders for nondurables                            |                      | 2.133***<br>(0.657)        |                            |
| Predicted nondurables VA,<br>nominal                  |                      |                            | 4.348***<br>(0.897)        |
| Constant                                              | 0.007<br>(0.008)     | 0.014<br>(0.016)           | -0.009<br>(0.016)          |
| Observations                                          | 71                   | 71                         | 71                         |
| Adjusted $R^2$                                        | 0.564                | 0.271                      | 0.376                      |

Notes: Predictors are growth rates relative to the previous quarter. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, 10% level.

Some coefficients in Table 7 plausibly reflect changes in manufacturing activity or cost: increases in new orders, consumer prices, or export prices, are associated with increases in expenditures on these intermediates. In the earlier tables, an increase in import prices was associated with higher expenditures on extrasectorals, presumably because they cost more. Here, an indirect effect seems to operate in the opposite: when import prices rise, less is spent on intermediates supplied within the domestic industry. This relationship is statistically strong for both durables and nondurables, and suggests that high import prices are high are associated with

reduced contemporaneous U.S. manufacturing activity. (This effect seems to outweigh a different pattern of manufacturers switching from imports to domestic suppliers.) PPI increases includes some increases in intermediate costs for the manufacturer, and seem to be associated here with sharply reduced durable goods manufacturing; this effect apparently outweighs any prices rises received by manufacturers.

Columns (2) and (3) show that new orders for nondurables are a good predictor of the use of same-industry intermediates in that sector, but the value-added measure predicted earlier in Table 3 is a better one.

The regressions in Table 7 show that some variables have the expected effect in predicting intrasectoral transactions, but do not provide highly accurate predictions. A more detailed analysis of intermediate purchases might produce more accurate predictions, and better estimates are available after the first GDP report is released, when official data on gross output and value added become available.

## Conclusion

Sectoral and value-added measures of output of the US manufacturing sector have meaningfully different quarterly growth rates. That can lead to confusion because the two sets of data can report significantly different estimates of labor productivity growth. Each measure provides some insight, but involves conceptual and empirical tradeoffs.

To understand and evaluate these differences, I divide the gross output of 2025-2022 manufacturing into six components and experimentally try to predict their quarter-to-quarter growth rates through regressions that use data that are publicly available before the first GDP report comes out. Reliable regressions can predict more than 80% of the variation in the quarterly growth in value added output in durable goods manufacturing. Other regressions can predict almost 50% of the variation in nondurables value added growth. The available variables predict components of output more accurately for durables than for nondurables. Overall growth in intermediates can be predicted accurately, but the shifts between the intrasectoral and extrasectoral components are not very accurately predicted.

The central research question about when sectoral output and value-added move differently can be answered. The key indicators that predict differences between the growth of sectoral and value-added output (that is, the extrasectoral intermediates) are import volumes, import prices, manufacturing employment, temporary help employment, and new orders for durables. When these increase, sectoral durable manufacturing output grows more quickly than value-added; when they decline, value-added tends to increase faster than sectoral output. Data available within 30 days of the end of a quarter can predict about 60% of the difference between the

quarterly sectoral and value-added output growth rates for durable manufacturing, and about 30% of that difference for nondurables. A notable example of such trends is the offshoring of computer and electronics manufacturing, associated with sharply reduced intermediate input flows, sharply declining prices, increases in sales, and reductions in U.S. employment; this brought about a sharp increase in domestic value-added while sectoral output rose more slowly.

Conceptually, these findings match several patterns discussed in the prior literature. The intermediates included in sectoral output measures rise in quarters when there is greater manufacturing activity, more outsourcing to temporary help services, or an increase in the costs of imported intermediates. Long term shifts toward offshoring of manufacturing production tends to increase value-added output relative to sectoral output.

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## Appendix A. Data sources and construction

The regression tables in this paper refer to data that come from many sources, which are described here. Most of the data is available to download. Data in levels and monthly data were converted to quarterly growth rates for the regressions.

BLS-published data for real sectoral output, from 2005-2022 were used. Those estimates have been constructed from Economic Census benchmarks every five years. Data published since then

have been largely extrapolated from the Economic Census of 2022, and are expected to be revised based on benchmarked data from the Economic Census of 2027. Sectoral output is modeled using annual benchmark data, and imputing seasonal while value-added output is benchmarked against official quarterly releases available with a lag of several months.

Quarterly value-added and gross output data come from BEA's web site; tables 106. These include industry expenditures into intangible capital (R&D, software, and artistic originals), and are before "redefinitions" which reallocate inputs and outputs of secondary production. Some of the BLS data used to distinguish intrasectorals and extrasectorals incorporates different definitions, such as Census value added by manufacture. I believe the differences induced in the estimates here of nominal intrasectoral and extrasectoral levels are small, and the differences in predicted growth rates smaller yet.

**Construction of estimates of nominal quarterly sectoral output and related intermediates:** For each quarter from 2005 on, for durables and nondurables separately, official estimates of current-dollar Value-added and Gross output come from BEA. For sectoral output data, I have official estimates of a real sectoral output index from BLS for each quarter, and nominal dollar levels for Economic Census years. This subsection explains how I've extended these source data to construct nominal dollar estimates for each quarter of intrasectoral and extrasectoral intermediates.

Intrasectoral transactions data are constructed at BLS for Economic Census years according to the methods described in Kovarik and Varghese (2019). They use the Import-Output and Supply and Use tables from BEA and the Census Bureau's Materials Consumed by Kind of Industry table. They make inferences about production from data on consumption. Imports are estimated based on import matrices from BEA's Input-Output Accounts. For years other than Economic Census years (years ending in 2 or 7), estimates are extrapolated based on Annual Survey of Manufactures data. For quarterly inferences about sectoral output, BLS extends previously known intrasectoral transaction data based on the Federal Reserve's Industrial Production indexes for the three months of a new quarter.

The nominal durable goods quarterly VA comes from BEA's regular table TVA105-Q, as it was available in summer 2026. That includes revisions since the first releases, and all these data are on the latest national accounts standards so R&D, software, and artistic and entertainment originals are capitalized in the same way every quarter whether or not they were reported that way at the time.

I have the current total values of nominal value-of-production for each year and BLS's published estimates of constant-dollar durable and nondurable sectoral output. From these I construct estimates of nominal intrasectorals and extrasectorals in three steps, described here for durables the analogous figures for nondurables are computed in exactly the same way.

(1) I infer from the published durable and nondurable sectoral output (SO) how much of each year's output was in each quarter. These proportions are close to .25 for any quarter, but with some variation; in Q3 of 2008 it fell to 22.7%.

(2) I impute nominal quarterly durables sectoral output for each quarter based on the durables nominal annual output for that sector, and the published proportion of annual output proportion from (1).

(3) Extrasectorals are then calculated as (SO minus VA) for each quarter, and intrasectorals are computed as (GO minus SO).

Other data used for prediction:

**IDEA indicators:** Monthly predictors are drawn from data supporting the Census Bureau's Index of Economic Activity (IDEA) program (Asturias et al., 2023, and [https://www.census.gov/econ/indicators/econindex/Census\\_IDEA\\_Methodology.pdf](https://www.census.gov/econ/indicators/econindex/Census_IDEA_Methodology.pdf)). I aggregated from daily data on levels to quarterly growth rates. These data were easy to download from the IDEA web site (<https://www.census.gov/data/experimental-data-products/index-of-economic-activity.html>)

**Price indexes:** CPIs, PPIs, and import and export prices indexes were retrieved from the BLS web site, and converted from monthly to quarterly growth rates.

Employment data came from the **Current Employment Statistics** data, downloaded from the BLS web site and converted from monthly to quarterly growth rates. This paper focused on data from the Employment Services industry, NAICS 5613. It is made up of subcategories for Employment Placement Agencies and Executive Search Services, Temporary Help Services, and Professional Employer organizations. Data is available on the employee counts, hours worked, and hourly pay for the Employment Services industry overall and for these three subsets of it. In the end, the variables used in regressions were for the Employment Services industry overall, which had approximately 7.8 million people in 2023. Dey, Houseman, and Poliva (2012) have analyzed this industry and estimated changes over time in the fraction working in manufacturing.

## Appendix B. Robustness tests

### A. Chow test of structural change

This section describes how I've tested for whether the relationships between our predictor and dependent variables change greatly over the 2005 to 2022 period, because if they have, it might not be safe to have a single linear regression for the whole period and use it as a prediction mechanism for later years. The coefficient 'structure' is usually stable, and exceptions are reported in the text.

The mechanism to determine this is the Chow (1957) test. It evaluates whether there is a particular breakpoint in the coefficients of a regression in a panel of data over a period. If the coefficients change in a statistically significant way in the year between two subperiods, the regression is said to have a “structural break” between them in that year.

The statistical test is of whether allowing different coefficients at an imagined breakpoint (e.g. 2008) greatly reduces regression residuals. If it does, that looks like a break.

- Technique: If overall regression is  $Y = a + b_1x_1 + b_2x_2 + e$
- Create dummy ‘g’ = 1 for later time period, and interact with x’s
- Estimate b’s from  $Y = a + b_1x_1 + b_2x_2 + b_3g + b_4*gx_1 + b_5*gx_2 + e$
- Then F-test for joint hypothesis that  $b_3=b_4=b_5=0$
- A test statistic under .05 rejects the hypothesis that there was no structural break in that regression and year at the 95% level. That tests for a particular breakpoint.
- Check for breaks from 2008 to 2019 for each regression, but not the first and last 3 years of the sample for which there is too little data in one subperiod to make a conclusion.

## **B. Collinearity of predictors**

Highly collinear predictor variables can produce unstable prediction regression models. They can be overly sensitive to small changes in correlated variables (Meyer and Martinez, 2018). This is diagnosed conveniently by the Variance Inflation Factor (VIF), which summarizes the degree to which the regressors predict one another. In the regressions shown here, the VIF was never much above 4.0, which is a standard level to check for, and suggests that collinearity alone was not a severe problem in applying these coefficients.

## **C. Seasonality checks**

Value-added growth for first quarters is higher than for other quarters, to a small but statistically significant degree. The pattern matches what was referred to as “residual seasonality,” which was addressed by an interagency team during the period under study . (Moulton and Cowan (2016) discuss how the problem was addressed; Glaser et al (2024) evaluate the effects of revisions to Q1 data on productivity estimates.) Predictive regressions here do not include any quarterly dummies, on the assumption that seasonal adjustment methods will prevent Q1 data from being especially high in the future.

## **D. Tests of behavior in the years with extreme change, 2008 and 2020**

The regressions shown were not generally sensitive to recession periods, and predictions are close to actuals, even for 2008 and 2020. Charts for the value-added predictions are below. As is common for linear prediction models, there is a small bias toward zero in the predictions.

**Chart B1: Predicted and actual durable goods value-added growth measures**

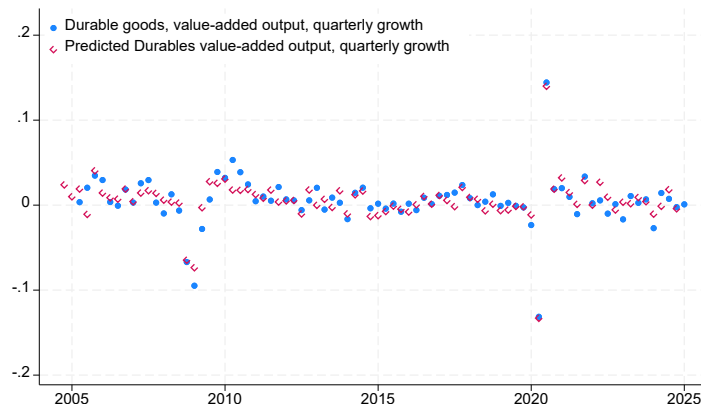
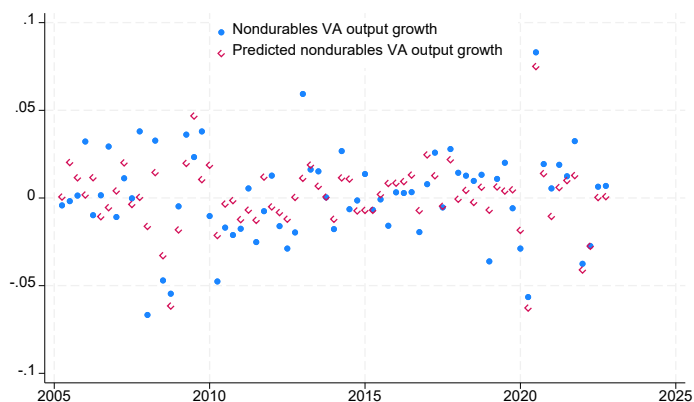


**Chart B2: Predicted and actual nondurable goods value-added growth measures**



## Appendix C. Related literature

The OECD has examined a variety of approaches to making immediate estimates (nowcasts) of productivity statistics across 40 countries. They review a substantial literature of methods and data, often not making nowcasts of output but rather productivity directly (Dorville et al, 2025). BEA conducts ongoing research on how to make nowcasts of output using a variety of data such as credit card use (Mallatt, 2025; Cornwall and Gindelsky, 2025). The Federal Reserve's Industrial Production Indexes incorporate much more data than was used here. Railroad traffic and supply manager survey data would be available.

The estimates shown in tables 3-7 in this paper do not use such sophisticated methods nor reach such levels of accuracy, but rather are intended to convey some basic patterns and estimates of output components.