

Labor Composition and the Recent Productivity Acceleration: Evidence From a Prototype Quarterly Industry Dataset

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Abstract Over the medium- and long-term horizons, the contribution of labor composition to labor productivity growth lags individual and societal investments in human capital and other demographic changes. At higher frequencies (e.g., quarterly), labor composition impacts labor productivity growth via short-run labor market dynamics that trade off skills to meet prevailing economic conditions. We employ a newly developed BEA research dataset on quarterly industry-level labor composition and find that: (1) at the quarterly frequency since 2005, labor composition growth accounted for about 14% of aggregate labor productivity growth (16% from 2005Q2 to 2019Q3 and 10% from 2019Q4 to 2024Q4); (2) small aggregate contributions of labor quality mask industry-level heterogeneity; and (3) at the higher frequency, results indicate that labor composition had important momentum at the end of 2024 that explains all of the late-period ALP acceleration. This last finding suggests that measuring industry-level labor quality could add useful information to analysis of the business cycle.

Keywords Aggregate productivity growth, labor composition, labor quality, business cycle dynamics

JEL codes E24, E32, J24

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1. Introduction

Labor productivity growth is a fundamental economic statistic. Understanding its growth and fluctuations is of primary interest to policymakers, business leaders, and economic analysts. While official data on U.S. productivity growth have been available at annual and aggregate quarterly frequencies for many years, there is growing demand across the statistical system for higher-frequency, industry-level data to evaluate rapidly evolving economic conditions. In this paper, we introduce a prototype quarterly dataset designed to illuminate the industry-level origins of labor productivity growth.

Labor productivity is typically defined as real output per hour worked.¹ Growth in labor productivity indicates that the workforce has become more productive, but aggregate output per hour alone provides no information regarding the underlying drivers of that change. Workers may become more productive through capital deepening (using more or better capital per worker) or through technological progress and organizational efficiencies (total factor productivity, or TFP). We provide new information at the quarterly frequency on a third primary driver: shifts in labor composition (or "labor quality"), such as changes in the educational attainment, age, and experience distribution of the workforce. While a rich literature examines the long-term role of labor composition in economic growth and annual labor quality contributions have long been part of official U.S. productivity statistics, the contribution of our prototype dataset is measuring industry-level labor composition changes at the quarterly frequency.

An important motivation for this work stems from the provocative findings in [Hobijn et al. \[2025\]](#), who develop a quarterly industry-level dataset to assess the sectoral origins of aggregate labor productivity change. Among their key results, they find that beginning in 2019Q4, the primary industry drivers of aggregate productivity growth shifted toward an emerging set of sectors, computer systems design, retail trade, data processing, and management of companies. Furthermore, they conclude that the majority of aggregate productivity variance is accounted for by increased variance in industry-level productivity growth.

The dataset we develop, described in detail in [Jang and Samuels \[2026\]](#), allows us to examine these findings through the lens of labor composition. We first convey the macro-level framing. Across medium-term multi-year averages, aggregate labor productivity (ALP) growth accelerated from an annualized average of approximately 1.2% over 2005Q2–2019Q3 to 1.8% over 2019Q4–2024Q4.² Over this window, labor composition change actually moved in the opposite direction, decelerating from a 16% contribution to ALP growth in the earlier period to roughly 10% in the post-2019 period. At the industry level, among

¹There are alternative definitions, such as real output per worker, but we focus on the widely used output-per-hour framework.

²Following standard timing conventions, 2005Q2 denotes annualized growth between 2005Q1 and 2005Q2. Thus, the period 2005Q2–2019Q3 measures cumulative annualized growth from 2005Q1 through 2019Q3.

the key sectors identified by [Hobijn et al. \[2025\]](#), only within management of companies did labor quality account for a meaningful share of productivity acceleration over these long averages. Moreover, while industry-level variance in labor composition contributions increased post-2019, it explains almost none of the cross-industry variance in overall labor productivity growth.

However, evaluating medium-term averages masks significant differences across periods. When evaluating short-term post-pandemic momentum by comparing a 4-quarter moving average (MA4) at the pre-pandemic peak (2019Q4) to the latest endpoint of our prototype data (2024Q4 MA4), a different dynamic emerges. Taking 2019Q4 as the final benchmark prior to COVID-19 and 2024Q4 as the current reading of productivity momentum, our prototype dataset reveals that the acceleration in aggregate labor productivity growth between these two periods is entirely accounted for by an acceleration in the contribution of labor quality. Our industry-level decomposition indicates that these gains were not uniform across the macroeconomy, but highly concentrated in approximately 10 sectors, led by retail trade, ambulatory health care services, miscellaneous professional and scientific services, and hospitals and residential care facilities. This contrast demonstrates that high-frequency, quarterly industry-level labor composition data are particularly vital for capturing short-term structural shifts and business-cycle momentum that long-horizon averages obscure.

Our paper builds upon a growing interest in high-frequency labor market dynamics. While [Stewart \[2022\]](#) investigated quarterly labor composition during the pandemic and documented sizable compositional effects, our dataset advances the discussion in four key ways: (1) it provides an updated time series extending through 2024, (2) it is explicitly constructed to maintain consistency with the official annual Industry-Level Production Account (ILPA) estimates, (3) it offers finer industry detail, and (4) it incorporates the balanced data-driven/econometric methodology detailed in [Jang and Samuels \[2026\]](#).

Finally, we note that this introductory paper does not attempt an exhaustive empirical analysis of the cyclicity of labor productivity or the extent to which quarterly labor composition dampens or amplifies macro fluctuations. Rather, our objective is to introduce this prototype dataset, outline the connection to labor productivity growth, and demonstrate its value through the applications we described above.

2. Labor Productivity Growth Accounting

In this section, we provide the growth accounting equations that link labor productivity growth to changes in labor composition.

With industry-level real value added labeled $Q_{VA,j}$ and hours worked in industry H_j , labor productivity is defined as:

$$LP_j = \frac{Q_{VA,j}}{H_j} \quad (1)$$

Taking log growth rates yields:

$$\Delta \ln LP_{j,t} = \Delta \ln Q_{VA,j,t} - \Delta \ln H_{j,t} \quad (2)$$

To understand the role of labor composition growth in the growth rate of labor productivity, we start with the sources of growth of industry level value added:

$$\Delta \ln Q_{VA,j,t} = \bar{v}_{L,j,t} \Delta \ln L_{j,t} + \bar{v}_{K,j,t} \Delta \ln K_{j,t} + \Delta \ln TFP_{VA,j,t} \quad (3)$$

where $L_{j,t}$ is industry-level labor input (not hours), $K_{j,t}$ is industry-level capital input (not capital stock), and $TFP_{VA,j,t}$ is industry-level value added-based TFP (not gross output based TFP growth).

The key to identifying the role of labor composition growth in labor productivity growth is the construct of labor input $L_{j,t}$. Labor input for industry j is defined as a Tornqvist index of hours worked by i different types of workers. This can be compared to total hours worked in the same industry H_j . In the parlance of [Jorgenson et al. \[2005\]](#), the difference between labor input growth and hours growth is referred to as labor quality growth because it captures substitution toward hours worked of more productive workers (also referred to as labor composition).³ Labor composition growth is defined as the growth in labor input $L_{j,t}$ not accounted for by the growth in raw hours worked ($H_{j,t}$).

$$\Delta \ln LC_{j,t} = \sum_i \bar{w}_{i,j,t} \Delta \ln H_{i,j,t} - \Delta \ln H_{j,t} \quad (4)$$

That is, labor input is defined as $\sum_i \bar{w}_{i,j,t} \Delta \ln H_{i,j,t}$, a Tornqvist index of hours worked across i worker types and raw hours worked is just a simple sum of hours worked by those same workers.

Using the above equations yields a decomposition of industry value-added-based labor productivity growth into the contributions of labor composition, capital deepening, and TFP growth as shown below:

³ It is important to note that this construct does not fully capture labor input heterogeneity or worker quality, but is a tractable approach that covers a long time series.

$$\begin{aligned}
\Delta \ln LP_{j,t} &= \Delta \ln Q_{VA,j,t} - \Delta \ln H_{j,t} \\
&= \bar{v}_{L,j,t} \Delta \ln L_{j,t} + \bar{v}_{K,j,t} \Delta \ln K_{j,t} + \Delta \ln TFP_{VA,j,t} - \Delta \ln H_{j,t} \\
&= \bar{v}_{L,j,t} (\Delta \ln L_{j,t} - \Delta \ln H_{j,t}) + \bar{v}_{K,j,t} (\Delta \ln K_{j,t} - \Delta \ln H_{j,t}) + \Delta \ln TFP_{VA,j,t} \\
&= \bar{v}_{L,j,t} \Delta \ln LC_{j,t} + \bar{v}_{K,j,t} (\Delta \ln K_{j,t} - \Delta \ln H_{j,t}) + \Delta \ln TFP_{VA,j,t}
\end{aligned}$$

The object of interest of this paper is $\bar{v}_{L,j,t} \Delta \ln LC_{j,t}$. This term represents the contribution of changes in the composition of the workforce to labor productivity growth by industry. We do not have data on capital input by industry; therefore we are not able to separately identify the contributions of capital deepening and TFP growth by industry. Thus, we group these terms together and decompose industry ALP growth as:

$$\Delta \ln LP_{j,t} = \bar{v}_{L,j,t} \Delta \ln LC_{j,t} + \text{other}_{j,t} \quad (5)$$

Finally, we rely on the production possibility frontier concept to aggregate across industries:

$$\Delta \ln LP_{Agg,t} = \sum_j \bar{w}_{V,j,t} \Delta \ln LP_{j,t} \quad (6)$$

$$= \sum_j \bar{w}_{V,j,t} (\bar{v}_{L,j,t} \Delta \ln LC_{j,t} + \text{other}_{j,t}) \quad (7)$$

$$= \sum_j \bar{w}_{V,j,t} \bar{v}_{L,j,t} \Delta \ln LC_{j,t} + \sum_j \bar{w}_{V,j,t} \text{other}_{j,t} \quad (8)$$

where $\bar{w}_{V,j,t}$ is each industry's weight in nominal aggregate value added (two period average share).

Quarterly measures of $\Delta \ln Q_{VA,j,t}$ are taken directly from BEA's industry accounts. Construction of the labor data is described in detail in [Jang and Samuels \[2026\]](#).

3. Results

We set the stage using [Hobijn et al. \[2025\]](#) as a point of departure. First, aggregate labor productivity growth has accelerated in the 2019Q4 period relative to the earlier period (our dataset begins in 2005Q2).

Using equation (6), ALP growth in the later period was about 1.8% per year in comparison to 1.2%.⁴ Note that our measures cover the entire economy (not just nonfarm business) to conform to the GDP statistics.⁵ Figure 1 shows industry contributions to aggregate labor productivity growth in the later and earlier periods to match the same basic figure in [Hobijn et al. \[2025\]](#) and confirms the emerging industry result (where the orange bar exceeds the blue). Retail, computer systems design, data processing, and miscellaneous professional services emerge as important industry contributors to ALP growth under this framing. This tabulation is also the basis for the variance result mentioned in the introduction; while not evident from this figure, the variance of the industry-level contributions increased in the second period relative to the earlier.⁶

Figure 2 shows that very little of this acceleration between 2005Q2-2019Q3 and 2019Q4-2024Q4 was driven by changes in industry-level labor quality contributions to ALP growth. As described above, this implies that over this period growth accounting attributes the change to other factors including capital deepening and TFP change. Also, in terms of variances, given the relatively low level contributions of labor composition to the macro economy in these periods, the increase in the variance as mentioned in [Hobijn et al. \[2025\]](#) is not accounted for by an increase in the variance of industry-level labor composition contributions; in fact, the variance of labor composition accounts for just over 1% of the variance of labor productivity contributions.

In Figure 3, we provide one example that is relevant for analysis of current trends in productivity growth. Figures 1 and 2 were pertinent for assessing medium-run trends (the 2019Q4-2024Q4). It is likely that this period could be analyzed without the use of higher-frequency quarterly data. In Figure 3, we compare a 4-quarter moving average of each industry's contribution to ALP growth in 2024Q4 (the last period in our sample) less the contribution in 2019Q4. With 2019Q4 interpreted as the latest read in the sources of productivity growth before the pandemic, the tabulation reveals important differences in the sources of productivity growth. First, comparing the trailing 4-quarter moving averages (MA4), aggregate labor productivity growth accelerated by 0.32 percentage points—from 1.73% annualized in 2019Q4 MA4 to 2.05% in 2024Q4 MA4. Notably, this entire acceleration was accounted for by the labor quality contribution, which also accelerated by 0.32 percentage points over the exact same period. This means that based on this particular tabulation, capital deepening and TFP growth, bottom up across industries, played no role in the ALP growth acceleration. Second, these gains were concentrated in a subset of industries, in particular retail trade, ambulatory health care services, miscellaneous professional and scientific services, and hospitals and residential care facilities. This emphasizes the importance of industry-level data.

⁴ Simple average of the quarterly annualized growth rates.

⁵ We adjusted the definition of real government value added for the implicit price of labor input, as in the ILPA.

⁶ A regression of each industry level observation on a constant, and a dummy variable for the later period puts a p-value of 0.022 on the late period dummy.

Figure 1: Industry Contributions to Aggregate Labor Productivity Growth

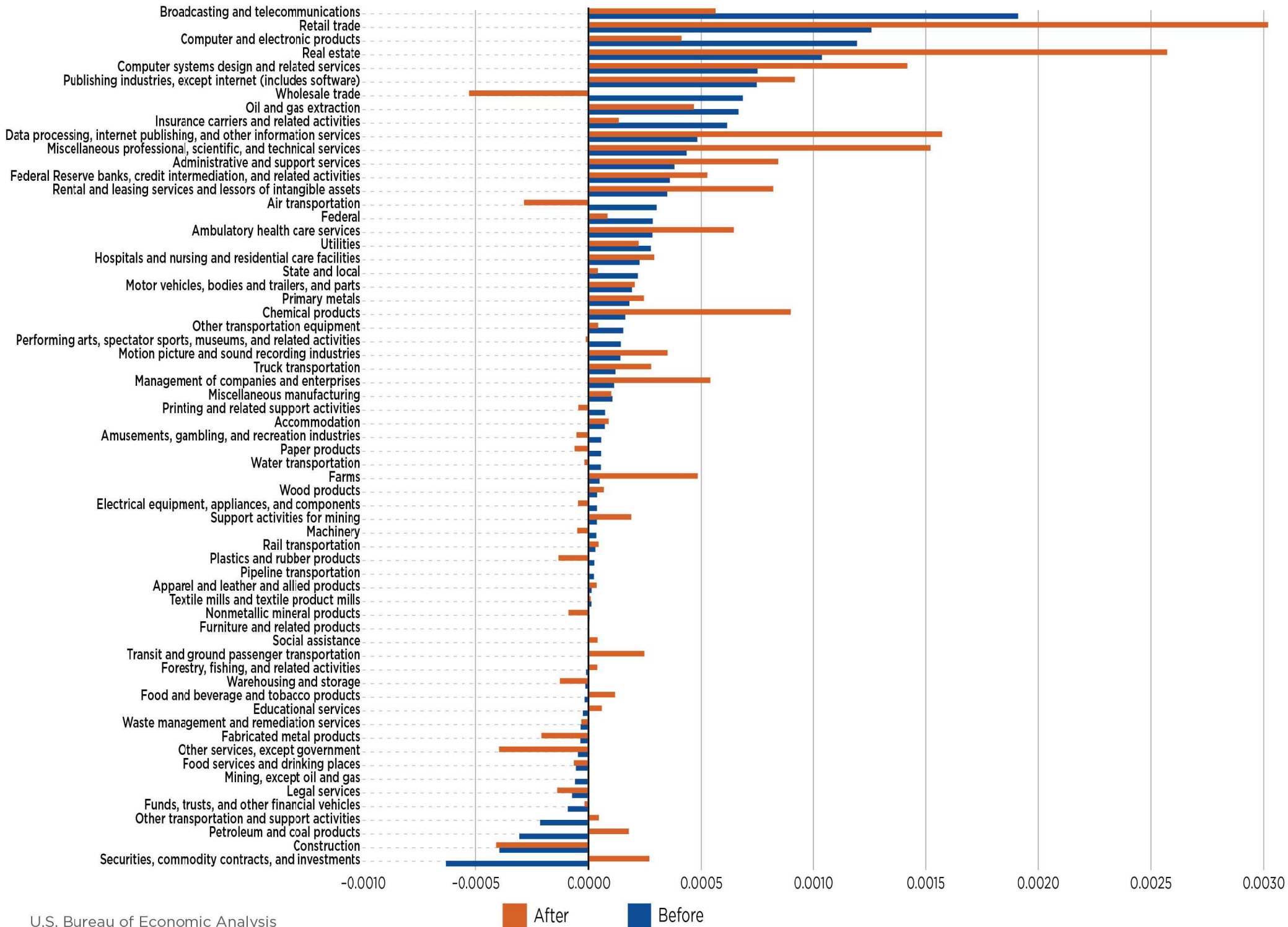


Figure 2. Contributions to ALP Acceleration

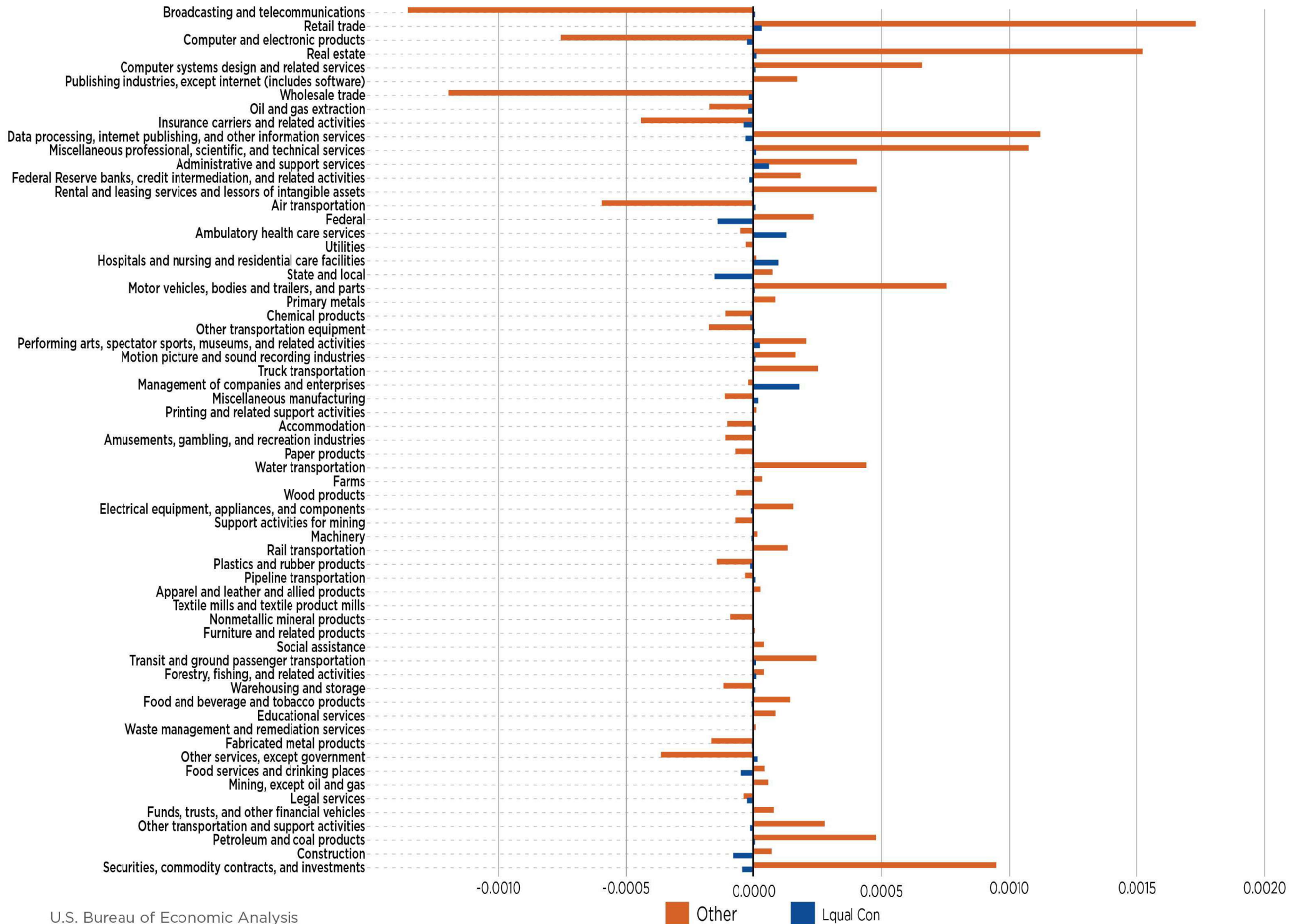
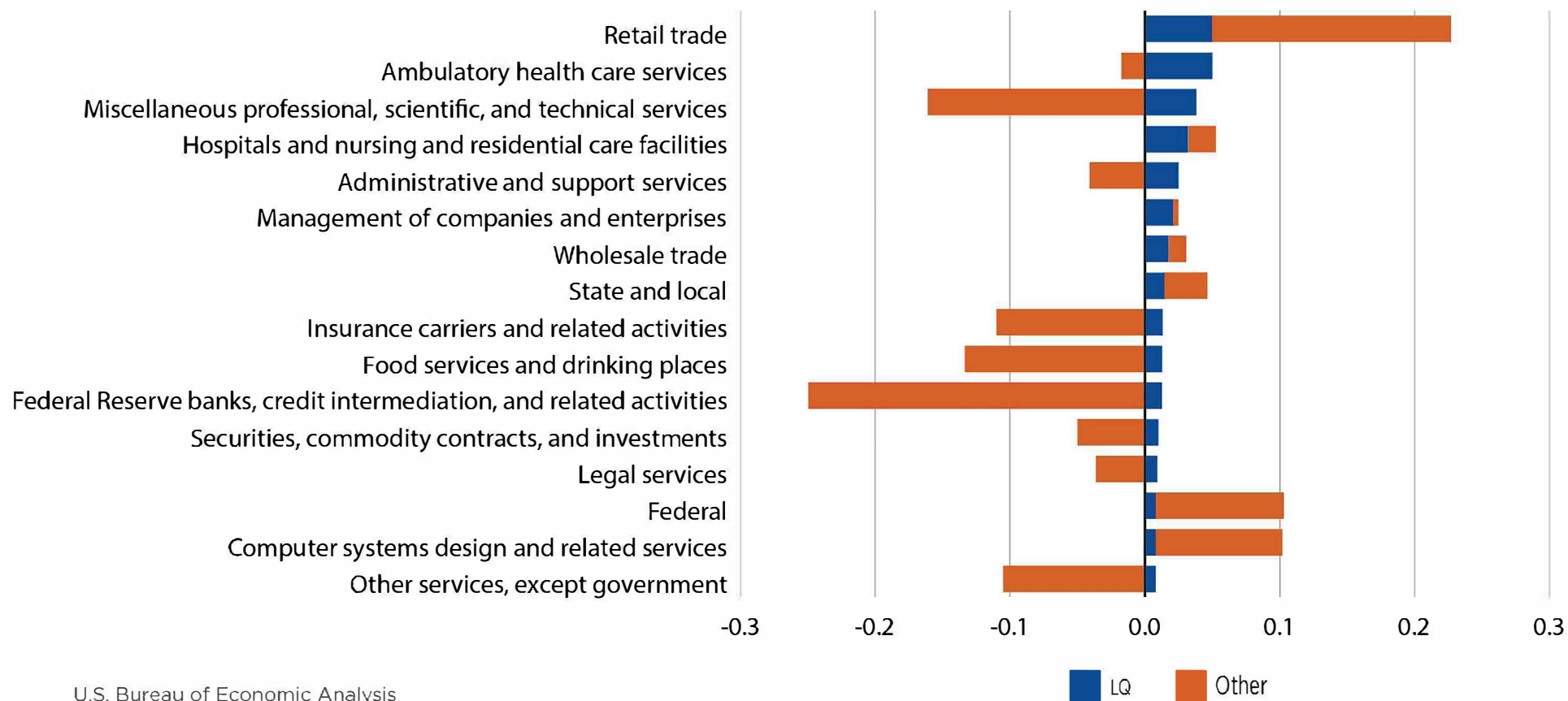


Figure 3: Top LQ Contributions to the Acceleration of ALP Growth 2024Q4 v 2019Q4



4. Conclusions

Labor quality growth over longer sample periods is mostly a stable contributor to U.S. labor productivity growth. But, based on the most recent results in our sample, we conclude that it is important to measure industry-level labor composition at the quarterly frequency to get higher frequency reads on the sources of labor productivity growth. We emphasize that the prototype data that we present does not address all of the issues that may be pertinent for measuring labor quality (for example how to measure worker effort, how to define the cross tabulation of worker groups, how to define wages for self-employed workers, etc.) but strikes a balance between using the methods in the official annual data and addressing small sample issues [Jang and Samuels \[2026\]](#). Going forward, important research remains to be done on the cyclicity of labor composition and what that means for assessing overall economic conditions.

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