Discussant Comments on "Innovation Growth Accounting" by Peter Klenow and Huiyu Li
Comments by John Haltiwanger

Understanding the determinants of innovation and productivity growth is a core open area of economics research. While enormous progress has been made in theoretical models of innovation accompanied by increasing use of firm-level data to quantify the nature of innovation and productivity many challenges remain. A key challenge is that much of the research using firm-level data has focused on firms with observable measures of the inputs into innovation (e.g., R&D expenditures) and direct measures of the success of innovations (e.g., patents). This approach focuses on a relatively narrow subset of firms and sectors where such observables are relevant. Most firms don't have report R&D expenditures or patents. It is implausible that it is only the firms with these observable measures of innovation that are solely responsible for the observed fluctuations in productivity growth from innovation. As evidence of this, a National Academy of Sciences report (Brown et. al (2005)) highlighting the limitations of R&D data reported that one of the most innovative firms in Retail Trade, Wal-Mart, reports no R&D expenditures in their 10K reports.

This paper takes an indirect approach to identifying innovation activity that overcomes these limitations. Using an innovative growth accounting framework that is motivated by a quality ladder model of innovation, this paper uses data on the employment growth rate distribution for universe of private sector, non-farm (hereafter private sector for short) establishments to quantify the contribution of creative destruction, own innovation and new varieties. The authors accomplish this important objective by using the Longitudinal Business Database (LBD) that tracks the employment dynamics including entry and exit, firm size and firm age of the universe of private sector establishments and their parent firms. This paper uses the LBD for the period 1982 to 2013.

The quantitative analysis yields many interesting results. These are well described in the paper so for the sake of brevity I highlight two of key results discussed in the abstract. First, they find that new and young firms punch more than their weight. Almost 50% of aggregate productivity growth over their sample period is accounted for by firms age<5 even though they account for only about 16% of employment. Most of this is coming from new variety introduction by startups and young firms. Second, in spite of this outsized role for young firms, they find that most of the surge in productivity in mid 1990s and then slowdown thereafter

accounted for by older firms. Here the primary contributor is own innovation by older firms.

Quantifying the contribution of innovation to economic growth for the entire private sector is a major step forward. However, the authors indirect approach using the LBD is implemented with a number of strong assumptions that are inconsistent with empirical evidence. Relatedly, the approach taken does not distinguish between the key distinct patterns in firm dynamics and productivity that vary by sector. These limitations imply that appropriate caution is needed in interpreting the quantitative results. The authors acknowledge many of these limitations and discuss addressing them as next steps. In the remainder of my comments, I discuss the evidence that implies that these limitations are likely quantitatively important. In turn, I discuss potential next steps in this promising research agenda.

To understand the limitations, it is helpful to review briefly the key assumptions of the framework and the accompanying identification approach. New products are identified through new establishments. New establishments are used to identify new varieties and creative destruction. Own innovation is identified via growth in employment of incumbent establishments. The framework and data permits heterogeneity in own innovation, arrival rate of creative destruction, step size by groups of establishments classified by firm age and firm size classes. A key strong assumption is that creative destruction is (CD) is random. That is, the rate of loss from CD is the same across all firm groups. Another key strong assumption is that there are no frictions that yield dispersion in marginal revenue products. Accordingly, in the simple framework used with employment as the only input, the model implies that there is no dispersion in revenue per worker across firms and establishments. Yet another strong assumption is that the framework treats all of the establishments and firms in the private, non-farm sector as contributors to final output via a single CES aggregator across products.

The assumption that CD is random implies that when Wal-Mart opens up a new store in a specific geographic location then any implied CD loss applies to all incumbent establishments in all sectors and locations. The evidence on establishment entry and exit as well as studies of the impact of entry of establishments on incumbent establishments implies that CD is both sector and location specific.

Figure 1 shows tabulations from the Business Dynamic Statistics (BDS) which reflects public domain tabulations by the U.S. Census Bureau from the LBD. The top panel shows the share of employment of entering establishments for the entire private sector (economy) and for

selected broad sectors.   The lower panel shows the share of employment for exiting establishments for the same sectors. These are two of the key moments used in the analysis in this paper (see for example Table 2 of the paper).   In these tabulations, the patterns reflect the combination of all firm age and size classes. The subperiods correspond closely to the subperiods used in this paper.[1]   It is evident that the Retail Trade sector exhibits especially high entry and exit shares on average.   This is consistent with the findings in Foster et. al. (2016) and Foster et. al. (2006) that firm expansion and contraction is dominated by establishment entry and exit in Retail Trade.   The industry-specific variation in entry and exit shares suggests that an entering establishment in say Retail Trade competes directly with other establishments in Retail Trade and not with establishments in other sectors. More direct evidence in Haltiwanger et. al. (2010) shows that when a new Big-Box store enters a local market the impact on other establishments in the same narrow Retail Trade sector and is very local.   That is, establishments in the same narrow Retail Trade sector and in close proximity are adversely impacted.   Local establishments in complementary sectors like Restaurants actually fare better upon such entry.

Figure 1 also shows that the decline in entry and exit in Retail Trade is more pronounced than other sectors.   Foster et. al. (2017) and Foster et. al. (2006) (and the cites therein) show that this reflects structural change in the Retail Trade sector away from single unit establishment firms to large national chains.   Single unit establishment firms have a much higher pace of entry and exit than the establishments of large national chains which accounts for the decline in the pace of entry and exit.   This structural transformation is linked to globalization and advances in IT that have enabled large national chains to develop global supply chains and efficient distribution networks.   During this period of structural transformation, aggregate productivity (measured as real output per worker) from BLS has exhibited especially robust growth (see Manser (2005)). The approach taken in this paper does not enable capturing this industry specific structural transformation.

A related issue for Retail Trade is that Foster et. al. (2006) and Foster et. al. (2017) show that revenue per worker for the entering establishments at large, national chains are about 30 log

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[1] The first subperiod is from 1987-1995 rather than 1982-95 as in the analysis in this paper.   The analysis in the paper considers three firm age groups: 0-5, 6-10 and 11+.   The latter two groups can only be defined directly from 1987 forward.   The analysis in the paper relies on an imputation that decomposes those two age groups for the period 1982-86.   I don't think this imputation and the difference in the first subperiod is critical since the empirical patterns for the moments for subperiods I construct from the BDS that can be compared to those in the paper are broadly similar.

points larger than the exiting establishments of the single-unit establishment firms that they are displacing within the same narrow sector. Such dispersion is at odds with the assumption of no dispersion in revenue per worker across establishments in the accounting framework in this paper.

The finding that revenue per worker exhibits considerable dispersion across establishments and firms within the same narrow sector is not unique to Retail Trade (see, e.g., Decker et. al. (2020)).[2] However, in Retail Trade the evidence exhibits a particularly systematic pattern with the structural change moving employment and sales away from low revenue per worker single unit establishments to high revenue per worker establishments of large, national chains. Moreover, this reallocation at the establishment level is accompanied by rising revenue per worker at the detailed sectoral level within Retail Trade.

In the paper, the authors defend the strong assumption of no dispersion in revenue per worker across establishments and firms by presenting evidence (from publicly available information) that for individual well-known firms such as Wal-Mart, Amazon, Google and Starbucks that their life-cycle patterns exhibit rapid growth in scale as measured by employment but relatively modest growth in revenue per worker. While this evidence is interesting it is not clear this is the most appropriate comparison. The evidence discussed above implies that such large national chain firms have much higher revenue per worker than the single unit establishment firms that they have displaced.

A distinct but important set of industries that have empirical patterns of firm dynamics and productivity growth that are inconsistent with the economy-wide patterns that are used in the accounting framework are the ICT industries and more generally the High Tech industries.[3] Fernald (2015) and Byrne et. al. (2016) provide compelling evidence that the surge in productivity in the 1990s and the slowdown is accounted for by the ICT producing and ICT intensive using industries. Figure 2 shows the distinct firm dynamics for the High Tech industries. Unlike the overall economy and sectors like Retail Trade, the High Tech sectors exhibited a surge in firm entry in the 1990s with the share of young firm activity growing substantially over this decade. In the post 2000 period, the share of activity accounted for by

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[2] See Figure 3b of Decker et. al. (2020).
[3] Here I am using the High Tech industry definition following Hecker (2005) which are the STEM intensive sectors. These industries so defined encompass the ICT (information and communication technologies) industries. The High Tech industries also include industries such as biotech.

young firms declines through 2017. Further evidence that young firms in High Tech sectors exhibit distinct dynamics over this period is seen by tracking the cohort of IPOs in the before the 1990s, during the 1990s and in the post 2000 period (see Figure A.6 of Decker et. al. (2016) and Ritter (2016)). The 1990s cohort is High Tech-intensive and rapidly becomes the dominate cohort in terms of the share of sales and employment that it accounts for among publicly traded firms.

Building on the findings in Fernald (2015) and Byrne et. al. (2016), Figure 3 presents the patterns of real labor productivity growth for the High Tech industries vs. other industries from BLS over this period of time.[4] The surge in productivity in the High Tech sectors during the 1990s and the slowdown in the post 2000 period (especially post 2005) is evident.

Further evidence there are potentially important connections between the firm entry and productivity surge in the 1990s in the High Tech industries is presented in Foster et. al. (2020). Using 4-digit NAICS industries that comprise High Tech and a diff-in-diff empirical specification, Foster et. al. (2020) present evidence that the surge in productivity growth in a given High Tech industry is proceeded by a surge in entry about 6-9 years before. Interestingly they also find that following a surge in entry in a given High Tech industry there is a substantial increase in revenue labor productivity dispersion initially (about 4-6 years after the entry surge), They argue that these patterns are consistent with the Gort and Klepper (1982) characterization of the important role of young firms in the experimentation phase of innovative activity. Gort and Klepper (1982) experimentation and learning are features missing from the current innovative accounting framework.

These patterns for High Tech raise questions about the analysis in the paper that suggests the productivity surge and slowdown is due to an own innovation surge and slowdown amongst mature firms. These inferences are based on matching the economy-wide moments that show a steadily declining pace of entry during the period of the productivity surge and decline. However, in the ICT (High Tech) industries exhibit both a surge in entry and productivity growth in the 1990s and a post 2000 decline in entry and productivity growth. Moreover, using detailed industry level data suggests an entry surge precedes the surge in productivity growth. Since

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[44] Fernald (2014) and Byrne et. al (2016) provide evidence of the outsized role of ICT on TFP growth. Figure 3 shows the patterns for labor productivity growth for High Tech and non High Tech. The patterns in Figure 3 for labor productivity for High Tech industries closely mimic the patterns for TFP for ICT. High Tech patterns are shown in Figure 3 to correspond to the young firm share evidence in Figure 2 for the High Tech industries.

the ICT (High Tech) industries played a dominant role in the productivity surge and slowdown, these industry-specific patterns need to be considered for explaining economy-wide patterns. The current paper does not attempt to account for these ICT (High Tech) patterns.   Another feature of the evidence on ICT (High Tech) that raises questions about the inferences from the accounting framework used here is the evidence from Fernald (2014) and Byrne et. al. (2016) that emphasizes the spillover effect of ICT on other sectors.   The accounting framework used here does not readily permit innovation of a general purpose technology like ICT that has such spillover effects.

Yet another reason that taking into account sectoral differences is likely important in this context is illustrated in Figure 4a.   Another important structural transformation over this sample period is the well-known shift in economic activity away from goods producing industries such as Manufacturing towards service industries including Retail Trade and other Service industries. This structural change is likely driven by forces (e.g., globalization) that are outside the scope of the accounting framework in this paper.   However, such structural change influences the targeted moments on establishment entry and exit dynamics by firm age and size that are used to quantify the respective contribution of different firm groups to economic growth. As can be seen in Figure 4b, the share of employment at mature firms is much higher than manufacturing than services.   This implies the shift from goods to services dampens the increase in the share of activity at mature firms.   It would be useful to consider the quantitative implications using firm dynamic moments that hold the composition of industries constant over the sample period.

Putting all of the pieces together, taking into account distinct patterns of firm dynamics and productivity growth by different sectors raises a variety of issues about the quantitative inferences drawn from the calibration of the innovative accounting framework to economy-wide moments.   An obvious next step in this promising research agenda would be calibrate the model on an industry-by-industry basis using moments on firm dynamic and productivity moments at the industry level.   The discussion above suggests that this likely requires using a sufficient level of industry detail (e.g., 4-digit NAICS).   Such an approach would have the advantage of making the creative destruction non-random (it would be industry-specific).[5]   Also, the CES

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[5] The post conference draft includes Appendix III that provides a framework that specified non-random CD.   This extension permits CD to be targeted to specific quality ranges.   This is a step forward but it has not been implemented empirically.   Moreover, it is unclear that this approach will be suitable for capturing the core idea that CD is both industry and location specific (especially in sectors such as Retail Trade).

aggregator assumption is more plausible at a sufficient level of industry-detail.   An attractive approach here would be to follow Hottman, Redding and Weinstein (2016) who use a CES structure within reasonably narrow product groups but then use a Cobb-Douglas aggregator to aggregate across sectors.   It would also be interesting to focus attention on the ICT (High Tech) industries in such an approach to evaluate how well this framework could account for the outsized role of these industries for the productivity surge and slowdown.

While an industry-specific application of this innovative accounting framework would be of considerable interest, other features of the framework require attention as well before more confidence can be put on the quantitative implications.   Revenue productivity exhibits considerable dispersion across establishments in the same narrow sector and also the differences in revenue productivity are systematically related to the firm dynamic moments that are at the core of this accounting framework.   The authors observe that the LBD does not include revenue measures at the establishment and firm level which is one of the reasons they do not pursue this line of inquiry.   However, other options using the Census firm and establishment level data are feasible.   Autor et. al. (2019) have used the Economic Census data for a wide range of industries on revenue and employment.   While the frequency is only every five years, such an analysis is feasible for the last several decades with revenue and employment at the establishment level. Moreover, the Economic Census data can be readily integrated with the LBD so moments that take the firm age and firm size heterogeneity into account as in the current analysis are feasible.[6]

Finally, it would be of considerable interest to compare and contrast the inferences that emerge from this framework with the large literature that uses direct approaches (i.e., with R&D and patents) to quantify the contribution of the different components of innovation to economic growth.   Yet another alternative and more direct approach is to track innovation as in Argente et. al. (2018) using product entry and exit from item-level product data.   To the authors credit, they have developed a framework that enables exploring these issues on a much broader basis than the research that uses a more direct approach.   Finding some way of reconciling what we are learning from these alternative approaches would have considerable value.   In considering such potential reconciliation, one of the seeming limitations of the approach in this paper

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[6] Decker et. al. (2020) also use administrative revenue data at the firm level in a revenue enhanced version of the LBD from 1996-2014.   The administrative data only provide revenue information at the firm level which would pose challenges for the approach taken in this paper.   However, adding moments based on firm-level variation could provide more discipline on the quantification analysis.

actually has some attractive features.   In this paper, new products are captured by new establishments.   At first glance, using direct measures of products would seemingly dominate. However, for many businesses opening up a new establishment in a specific location is a form of innovation (offering access to the products and services to consumers at this specific location). Keeping this location-specific feature that inherently is connected to establishment entry and exit should be part of the research agenda going forward.

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Figure 1　Moments of Establishment Entry and Exit Share for Selected Sectors

A. Entry Employment Share (Employment from Entering Establishments/Total Employment in Sector)
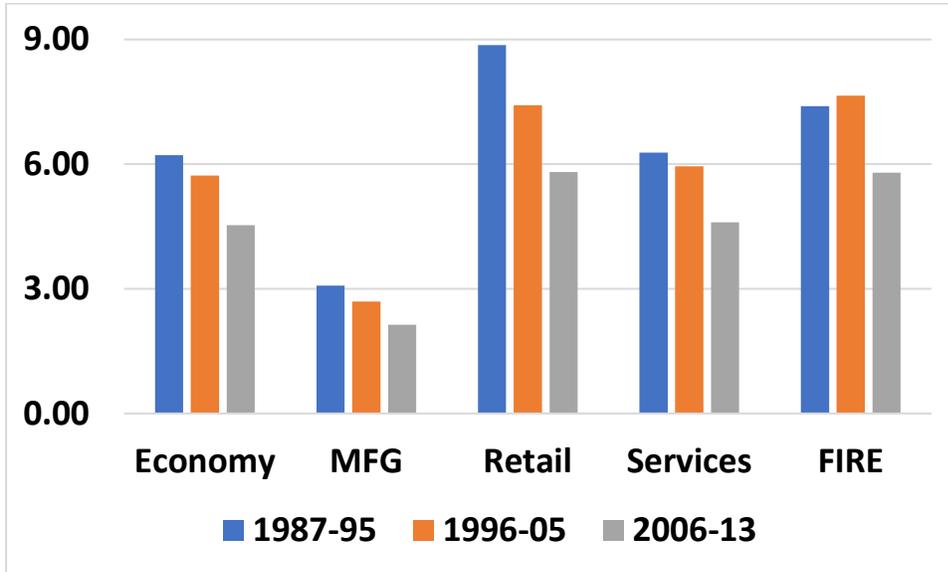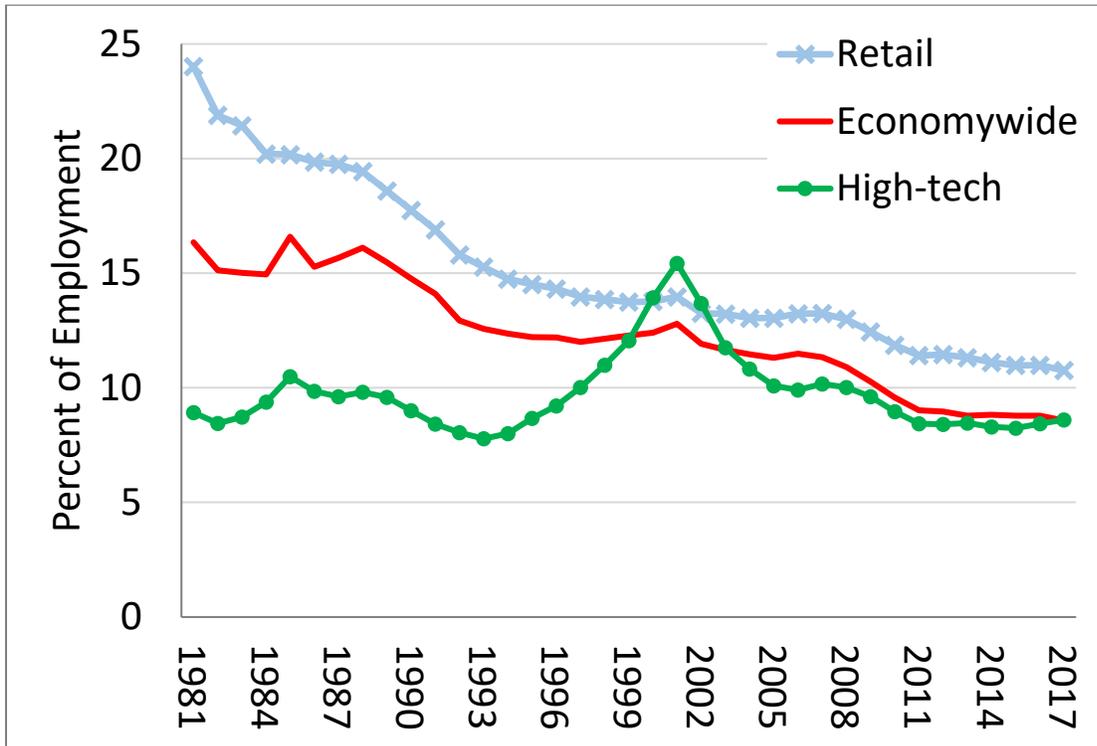

B. Exit Employment Share (Employment from Exiting Establishments/Total Employment in Sector)
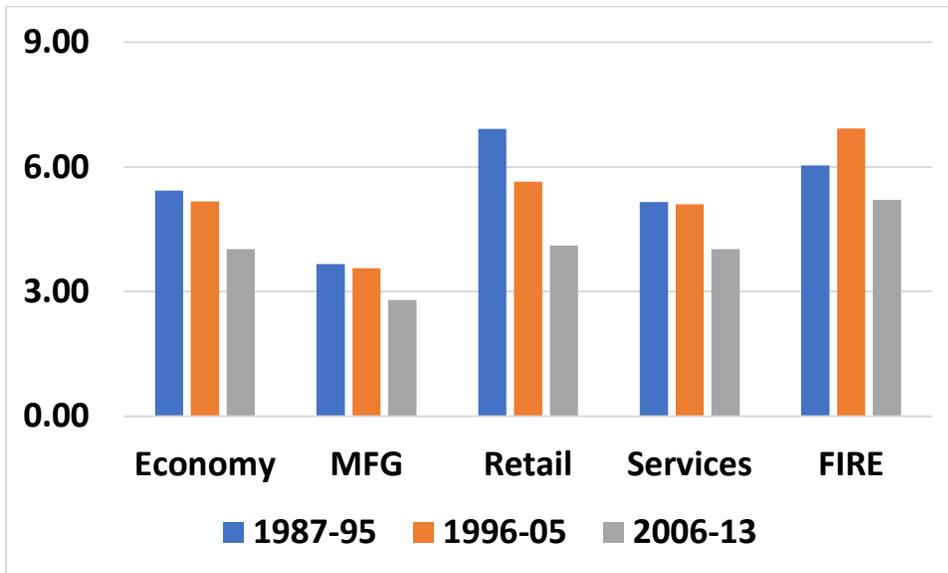
Source:　Tabulations from the BDS.

Figure 2. Percent of employment at Young (Age<5) firms by Selected Sectors

Source: Spliced series from LBD based tabulations in Decker et. al (2018) and tabulations from the Business Employment Dynamics (BED) from BLS.
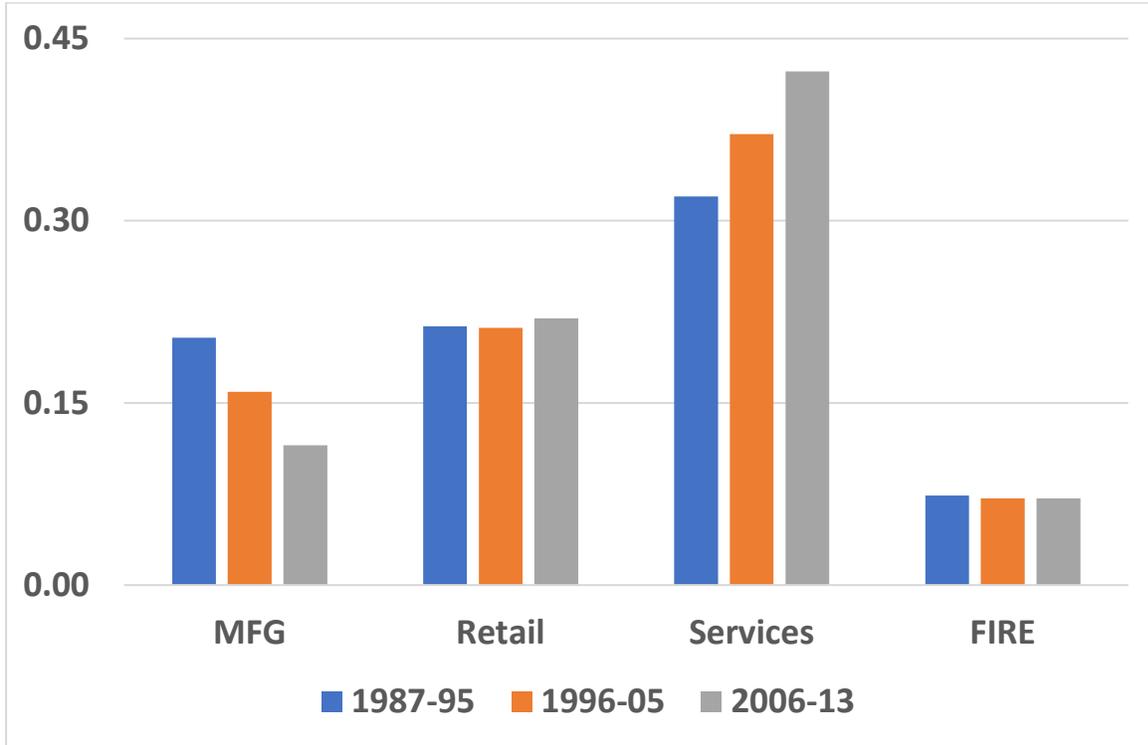
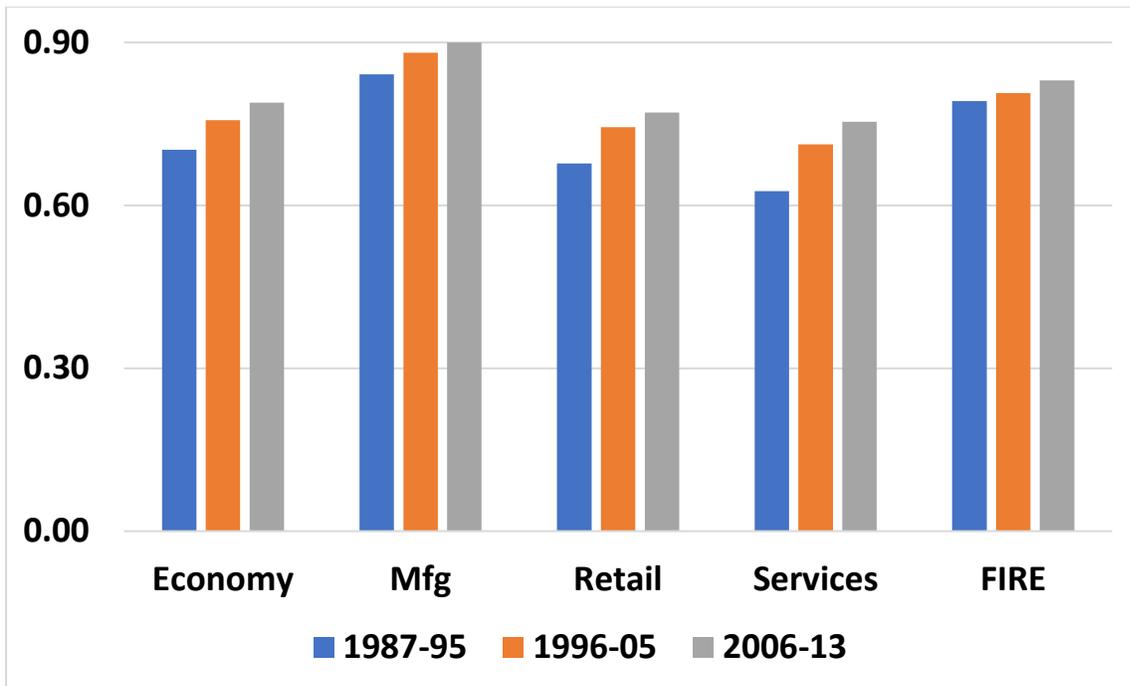Figure 3. Growth Rate in Output per Hour (Average Annual for Reported Subperiods)
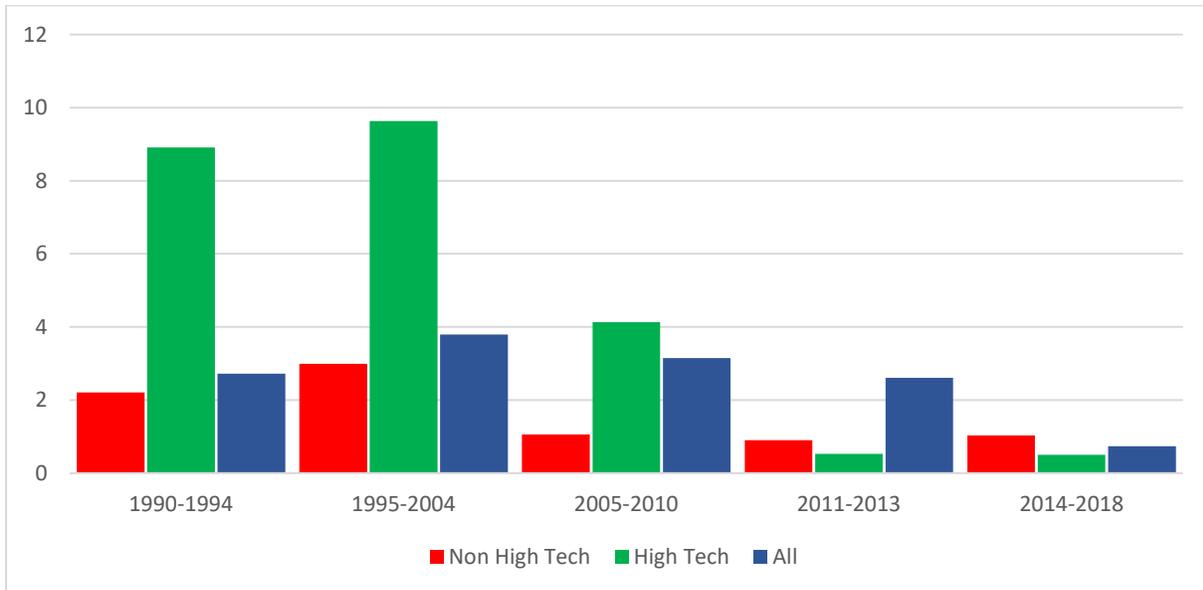
Source: BLS industry productivity statistics.

Figure 4.

A. Employment Shares of Economy-Wide Employment by Selected Sectors and Subperiod

B. Employment Shares of Age 11+ Within Sectors

Source: Tabulations from the BDS.