Modeling Aggregate Productivity at a Disaggregate Level: A First Look at Estimating Recent MFP Growth using a Sectoral Approach

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1. Introduction

As the step-up in U.S. productivity in the mid-1990s became evident, research on productivity surged. Although the new work on productivity spanned many literatures, a common organizing principle for much of the analysis was the Solow-Jorgenson-Griliches neoclassical growth accounting framework. This emphasis was especially evident in studies that concentrated on identifying the role of information technology (IT) in the step-up. Although some of the work on productivity and IT was conducted using detailed industry-level data (Jorgenson and Stiroh 2000), others used macroeconomic time-series data at only the broadest levels of disaggregation (Oliner and Sichel 2000) and obtained generally similar results.

But IT has not been the only important economic force that has been influencing productivity growth in recent years. Triplett and Bosworth (2004) show that, while multi-factor productivity (MFP) growth in the IT-producing industries has been very high, many non-IT services industries also had substantial MFP growth in the late 1990s. Moreover, the authors argue that the contribution of many dynamic services industries to the step-up in MFP growth is obscured in macroeconomic productivity data. Jorgenson, Ho, and Stiroh (2005) used a dataset that represented services industries in more detail than in their earlier work and made a similar point.

Many services industries had flat or declining trends in labor productivity for twenty or so years before the pick-up in productivity became evident (Corrado and Slifman 1999). It is therefore not surprising that disaggregate data were needed to to establish that the increase in productivity in the United States in the late 1990s went beyond the production and use of IT and was based in, many, but not all services.[1] Moreover, the "use of IT" story also is largely a services phenomenon (Stiroh 1998, Triplett 1999), and knowing which industries have been investing in the newer technologies requires disaggregate information. The variability in the diffusion of new technology and innovation across ranges of products is well documented (Mansfield

[1] This statement refers to the conventional representation of IT in the neoclassical growth accounting framework, which does not rule out the existence of externalities (or network effects) from IT. If such effects are present, the conventional framework will attribute them to MFP.

1968, Gort and Klepper 1982) and has, in some sense, long suggested that industry level data should be studied to detect and identify changes in productivity.

Given the macroeconomic importance of prospects for aggregate productivity (especially MFP), this paper addresses the question: Can information on recent industry productivity developments be used to update estimates of the trend in aggregate MFP growth? Unfortunately, data hurdles have inhibited the analysis of recent productivity change in the United States at a disaggregate level for many years. And currently there are additional complications—mainly the transition of the U.S. industry level data to a profoundly new classification system (NAICS)—that further inhibit the analysis of the current data.

One longstanding hurdle in disaggregate productivity analysis is the lag in availability of data and information required for the estimation of MFP at the industry level. In recent years, however, the Bureau of Economic Analysis (BEA) expanded and sped up the issuance of it industry accounts, input-output information, and capital flow tables. These are key ingredients both to disaggregate productivity analysis and to the compilation of capital services measures for the aggregate MFP statistics compiled by the Bureau of Labor Statistics (BLS). But, these data and information still lag several years.[2]

Moreover, as a result of the move to NAICS, substantial portions of the basic underlying source data used to estimate industry productivity (mostly in services) have a break in their time series or are available for a relatively short number of years. Although the BEA recently issued its GDP-by-industry estimates on a NAICS basis back to 1987, the effort required many assumptions (Yuskavage and Pho 2004). And, beyond the switch to the new industry classification system, BEA also recently introduced new estimating methods for the GDP-by-industry data, which in itself restricts the length of the time series available for analyzing trends in industry productivity.[3] All told, it is hard

[2] As of this writing, the most recent BEA data for industry output, intermediate inputs, investment and capital stocks are available on a NAICS basis from 1987 to 2003 (last updated in April 2005) and are consistent with the NIPAs issued in July 2004. BEA's data on NAICS employment are from 1998 on. Their data on NAICS hours begin in 2000 and are available at only the broadest level of aggregation.

The BLS aggregate multi-factor productivity estimates are available from 1948 to 2002 and were last issued in February 2005. The BLS has recently announced, however, that it will issue more timely estimates using simplified methods (Meyer and Harper 2005).

[3] The BLS also issues more-or-less complete datasets with disaggregate productivity measures, but because we use and draw upon studies that use the BEA's data (Corrado and Slifman 1999; Bartelsman and Beaulieu 2003; Triplett and Bosworth 2004), we emphasize the BEA data in this study. For a review of

not to suspect that industry-level productivity estimates calculated from the available, still somewhat fragmented, historical NAICS data likely contain an unusual degree of noise.

In this paper, we estimate industry-level productivity using the available data, but then we aggregate the results to six sectors that we believe both illuminate key trends and developments in productivity in the United States as well as traverse some of the worst breaks and noise in the data. We show that the six sectors have highly divergent trends in MFP growth, a result that we believe strongly suggests the disaggregate data are useful in assessing the current trend in aggregate MFP.

That said, to compute our industry productivity measures in a desired way, it was necessary to "fill in" many holes in the available data, and we did this using the tools of the FRB productivity system (Bartelsman and Beaulieu 2003). One major task we faced was generating estimates of employment and hours according to BEA's concepts and NAICS industry hierarchy prior to the late 1990s. Another was updating the Bartelsman and Beaulieu (2005) labor quality adjustments to conform to NAICS. As a consequence of these efforts, a detailed SIC-to-NAICS concordance for non-manufacturing industries is a by-product of our work.[4]

The plan of this paper is as follows: The next section spells out our theoretical framework, and that is followed by a section that reviews how the data and structure that we use are targeted to the analysis of productivity developments at the aggregate and sectoral level. We then present and analyze our sectoral results.

2. MFP at the aggregate and industry level.

Aggregate and industry-level productivity is related using the framework of Domar (1961), which was further developed by Hulten (1978) and Gollop (1979). The Domar framework expresses aggregate MFP growth as a weighted average of industry-level

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the statistical and conceptual differences among the various BEA and BLS datasets, see Fraumeni, Harper, Powers, and Yuskavage (2005).

[4] The SIC-to-NAICS non-manufacturing concordance used in this version of the paper (October 2005) is not final. Although our results are preliminary in this regard, we believe it unlikely the incorporation of the final concordance will materially affect our conclusions.

For manufacturing, we have incorporated the Bayard and Klimek (2004) concordance that was derived from Census Bureau microdata for the rebuilding of the Federal Reserve's IP index back to 1972 using industry data classified according to NAICS.

MFP growth rates and has been used in several prominent studies of U.S. productivity growth (e.g., Jorgenson, Gollop, and Fraumeni 1987, and Gullickson and Harper 1999).

Definitions and notation are introduced in table 1. Noting that bolded letters denote growth rates in real terms and that the subscript "T" refers to the "total" economy, the items in the table can be used to illustrate the Domar result that the rate of change in aggregate multi-factor productivity, $\boldsymbol{MFP_T}$, can be expressed in terms of (and calculated using) either aggregate or disaggregate measures. At the aggregate level, multi-factor productivity can be obtained residually from aggregates of sectoral output and inputs:

(1) $$\boldsymbol{MFP_T} = \boldsymbol{S_T} - \boldsymbol{I_T} \; .$$

Aggregate multi-factor productivity can also be obtained as:

(2) $$\boldsymbol{MFP_T} = \sum_{\boldsymbol{i}} \frac{S_i}{S_T} \boldsymbol{MFP_i}$$

where

(3) $$\boldsymbol{MFP_i} = \boldsymbol{S_i} - \boldsymbol{I_i}$$

and $$\sum_{\boldsymbol{i}} \frac{S_i}{S_T} > 1.$$

The framework uses the concept of sectoral output (S_i, defined as the gross output of a sector or industry less the amount produced and consumed within the industry or sector; see table 1) to model production for an industry or a sector. This output concept has an interesting property: Although it is essentially identical to gross output at the detailed industry level, as we move up a hierarchy of industries, sectoral output counts only what we are interested in—the amount of goods and services available after stripping out what is used up by the sector in production—and moves closer and closer to value added. Indeed, aggregate sectoral output differs from GDP only in that sectoral output includes imported intermediate inputs.

Sectoral output is an especially useful concept at an intermediate level of aggregation, the emphasis of this study. If we were only interested in moving from the individual industry level to aggregate MFP, it would not be necessarily to use sectoral

Table 1. Definitions and Notation

Gross output	Y_i	Shipments plus inventory investment for goods producers, or revenue for service providers. The cost of goods sold without further processing is also excluded, which is important for the trade industries.
Intermediate inputs	N_{ji}	Purchases by industry or sector *i* of the output of industry *j* (*j* = 1,…*J*) to be used as an input to production. Examples include expenditures on steel by automakers, electricity by retailers, and legal services by banks. Includes imports (industry *J*)
Value added $V_i = Y_i - \Sigma_j N_{ji}$ $= L_i + K_i$	V_i	Gross output less intermediate inputs, equal to the sum of income paid to all factors of production other than intermediate inputs. If capital and capital income are measured appropriately, equals the sum of the cost of labor (L_i) and capital (K_i) inputs.
Sectoral output $S_i = Y_i - N_{ii}$ $= L_i + K_i + N_{ij,j\neq i}$	S_i	Gross output less the consumption of intermediate inputs *produced within the industry (or sector)*, or goods and services produced by industry or sector *i* and shipped to other industries or sectors (or final demand). Also, equals sum of the cost of labor, capital, and intermediates "imported" from other industries or sectors ($N_{ij,\, j\neq i}$).
Sectoral inputs (real) $s_i^l\, \boldsymbol{L_i} + s_i^k\, \boldsymbol{K_i} + s_i^n\, \boldsymbol{\Sigma_j N_{ij,j\neq i}}$	$\boldsymbol{I_i}$	Share-weighted growth of the real inputs to production (labor, capital, intermediates from other sectors) for an industry or sector.
$s_T^l\, \boldsymbol{L_T} + s_T^k\, \boldsymbol{K_T} + s_T^n\, \boldsymbol{N_{TJ}}$	$\boldsymbol{I_T}$	Share-weighted growth of real inputs to production for the total economy (sector *T*).
Value-added inputs (real) $v_i^l\, \boldsymbol{L_i} + v_i^k\, \boldsymbol{K_i}$	$\boldsymbol{R_i}$	Share-weighted growth of real value-added inputs (labor and capital) for an industry or sector.

Note—Plain upper case variables are values; bolded variables are growth rates in real terms; and plain lower case variables are shares.

output to calculate MFP.[5] However, because we wish to illustrate the role of "intermediate level" sectors in the productivity performance of the overall economy, we find using sectoral output desirable because it accounts appropriately for the way in

[5] MFP calculated using sectoral output is related to MFP calculated using gross output by a factor of proportionality equal to the ratio of gross output to sectoral output. Note also that the rates of change in aggregate real value added and sectoral output have been very close for the U.S. economy (Gullickson and Harper 1999), at least historically. Thus, the relationship between industry and aggregate productivity can be studied by implementing (2) with MFP_i's calculated using gross output and using Y_i/V_T (gross output relative to aggregate value added) as "Domar" weights. This general approach has been used in many studies, including Triplett and Bosworth (2004).

which innovations in upstream industries contribute to both intermediate aggregates and to total MFP. Sectoral output also illuminates the relative importance of a sector's consumption of goods and services produced by other sectors (including imports), a useful property in view of the ongoing trends in outsourcing/offshoring and their potential impact on productivity.

We thus calculate industry-level multifactor productivity using (3). Sectoral output is derived from the BEA GDP-by-NAICS-industry data on gross output and purchases of intermediates, in conjunction with the available information in input-output (I-O) accounts.[6] Capital input measures were derived using BEA estimates of capital stocks by industry, which are available from 1987 on.[7] Labor input measures are hours worked adjusted for composition ("quality") as outlined in Bartelsman and Beaulieu (2005). As indicated previously, however, the underlying data for the labor series contain several breaks, and it was necessary to use numerous basic data sources (Census, BEA, and BLS) and the tools of the FRB productivity system to develop the industry-level labor input series used in paper.[8]

3. Measures of output and inputs for major sectors and for industries.

Using detailed industry data, we construct MFP for six major sub-aggregates of the total economy in a manner described above. Differences between our measures and official MFP may depend on differences in source data, differences in methodology, and differences in definitions of the aggregates for which official statistics are compiled and published.

The official multifactor productivity statistics for the United States are compiled by applying (1) to data for "major" sectors, the private business sector and the private nonfarm business sector.[9] In order to use (2) to analyze and decompose the sources and

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[6] We use the benchmark I-O account for 1997 and the annual I-O accounts for 1998 to 2003. We intend to include information from benchmark accounts for earlier years in the final version of this paper.

[7] We would prefer to replicate the methods used by BLS and calculate productive stocks for use in our capital input measures, but the published data on investment by NAICS industry only begin in 1987 and are generally insufficient for this purpose.

[8] As previously indicated, this part of our work is most subject to further change.

[9] The formula that is used by the BLS to compute aggregate MFP is a little more complicated than (1) in that it reflects various reconciling items (selected excise taxes and subsidies) in the national accounts. See Fraumeni, Harper, Powers, and Yuskavage (2005).

trends in productivity in these “total economy” measures, we thus face several issues. One is the closeness of the methods used for constructing the disaggregate inputs to the methods used by the BLS for constructing its aggregate measures of labor and capital inputs. A second is whether output for the set of industries being analyzed closely aggregates to the output of major sector of interest.

The methods used by the BLS to calculate capital input are based on building the measures from industry-level data. Their methods and approach follow a long literature (Jorgenson and Griliches (1967) and many later studies by Jorgenson and coauthors) that we are able to closely approximate. The BLS methods used to derive labor composition (or labor “quality”) adjustments to hourly labor input are not built from industry data, however. We thus employ alternative, industry-based methods (Bartelsman and Beaulieu 2005) that are similar to methods used Jorgenson and coauthors (see Jorgenson, Ho, and Stiroh 2005, for a recent example). Our aggregate labor input measures will thus differ from those issued by the BLS both because our labor composition (“quality”) effect will not necessarily be the same as BLS and because of industry-mix effects. In practice, we find that industry-mix effects, after controlling for labor composition, are relatively small.

The industry composition of the standard aggregates used in macroeconomic productivity analysis is another issue. Output in the private nonfarm business sector is obtained by subtracting the output of farms, households, nonprofits, and government from GDP. Three of these items are “industries” in the BEA’s GDP-by-industry system. However, the nonprofit sector is not an industry. It is a sector composed, in principle, of portions of each private industry in the economy. Thus, in order to use (2) to decompose productivity in the private nonfarm business sector by industry, the underlying industry data need to be further disaggregated into the portions that operate in the business and the nonprofit sectors, respectively. That is, we need:

$$Y_i = Y_i^{Business} + Y_i^{Nonprofit}$$

and so on, for each industry-level variable listed in table 1.

In practice, the output of the nonprofit sector in the United States is not all that large, but the sector’s activities are concentrated in selected services industries (education, health, social services organizations) and account for more than 10 percent of all private nonagricultural employment. While the inclusion (or exclusion) of the nonprofit sector in major aggregates will have only a small impact on the resulting figures (though more so on productivity than on output), the sector will have noticeable impact on an intermediate aggregate of services industries. In our work, we have exploited the available data to further disaggregate BEA's industry accounts to include a nonprofit segment in selected services industries. These segments are then excluded (along with government, etc.) in building the industry hierarchy that we use for our productivity analysis.

Table 2. Relation between GDP and private nonagricultural business excluding housing, 2003

	Value added	Employment[3]
	(billions)	(thousands)
GDP	10,971.3	133,686
Private nonagricultural		
Business	8,118.9	99,873
Other domestic producers	2,852.4	33,813
Agriculture	113.9	2,320
Nonfarm housing[1]	864.9	1,118
Nonprofits[2]	452.7	10,402
General government	1,276.3	18,201
Government enterprises	144.6	1,772
Memo:		
Private nonfarm business	8,195.2	

Source—Bureau of Economic Analysis.
1. Includes residential real estate in addition to owner-occupied housing.
2. Selected industries (authors' calculations).
3. Persons engaged in production (BEA).

The industry hierarchy that we use does not precisely aggregate to the BLS private nonfarm business sector. It aggregates to "private nonagricultural business excluding housing," which we will term for short, private nonagricultural business. The relationship of this aggregate in terms of value added and employment is shown in table 2. The sector we analyze does not materially differ from the official productivity aggregate: The entire agricultural sector (rather than just farms) is excluded; the entire nonfarm housing sector (rather than just owner-occupied housing) is excluded; and our own nonprofits aggregate (rather than the official, larger aggregate) is used. All told, the value added and employment in the private nonagricultural business sector closely approximates the value added and employment in the private nonfarm business sector (shown as a memo item in the table). Over time, the rates of change in real value added in the two aggregate sectors (not shown) also are very similar, but a wedge opens up in the later years.

When the industry-level results from (3) are then fed through our private nonagricultural business industry hierarchy and aggregated according to (2), the rates of change in the resulting time series for MFP are reasonably close to the official figures, as shown in table 3.[10] As may be seen, the differences between our MFP measure and the official MFP measure, though consistently higher, are mostly attributed to differences in output measurement in the later years, although input measurement differences also contribute in the earlier sub-period. As suggested by our previous discussion, most of the differences are in the labor input component although these are not parsed out in the table.

Table 3. Multifactor productivity, annual percent change, 1987 to 2003

	1987 to 2003	1987 to 1995	1995 to 2003
1. MFP, this paper[1]	1.13	.78	1.48
2. MFP, BLS/OS[2]	.97	.61	1.32
		—percentage points—	
3. Line 1 less line 2	.16	.16	.16
Contribution of differences in:			
4. Output measurement	.21	.03	.40
5. Input measurement[3]	- .05	.13	- .24

1. Private nonagricultural business sector. See table 2.
2. Private nonfarm business sector. Data include the unpublished update to Oliner and Sichel (2000) reported in Corrado, Hulten, and Sichel (2005).
3. Inputs measured in this paper less BLS inputs.

4. Sectoral decomposition of output and productivity.

The industry hierarchy that created the results shown in table 3 also created aggregates for six major groups of industries within the private nonagricultural business sector. These sectors are high-tech; construction; industry (excl. high tech); distribution; finance

[10] Note that because we use data through 2003—one more year than included in the currently published BLS data—we augment the BLS figures with the unpublished update to Oliner and Sichel (2000) reported in Corrado, Hulten, and Sichel (2005).

and business services (excl. high tech); and other services. Their relative size according to several metrics is illustrated in the table 4, and the footnotes to the table give more information on the industry composition of each group.

Table 4. Private Nonagricultural Business Hierarchy and Relative Sizes, 2003

	Sectoral Output					
		Deliveries to:				
billions of dollars	**Total[1]**	**Final Users**	**PNB Sectors**	**Gross Output**	**Value Added**	**Empl.[2]**
Private nonagricultural	(1)	(2)	(3)	(4)	(5)	(6)
business sector	8,889.0	8,889.0	0.0	14,572.1	7,776.8	97,277
High-tech[3]	685.8	593.1	92.7	776.6	373.2	3,162
Excl. High-tech	8,546.4	8,295.9	250.5	13,795.6	7,403.6	94,065
Construction	953.8	823.4	130.4	954.9	501.3	8,450
Industry[4]	3,094.0	2,354.2	739.9	4,248.9	1,677.7	14,979
Distribution[5]	2,130.6	1,455.9	674.7	2,634.8	1,735.1	24,462
Fin. and Bus.[6]	2,760.5	1,903.8	856.7	3,474.4	2,107.2	22,592
Services, other	2,213.5	1,759.7	453.8	2,482.6	1,382.2	23,580
Shares (percent)						
High-tech	7.7	6.7	---	5.33	4.80	3.25
Construction	10.7	9.3	---	6.55	6.45	8.69
Industry	34.8	26.5	---	29.16	21.57	15.40
Distribution	24.0	16.4	---	18.08	22.31	25.15
Fin. and Bus.	31.1	21.4	---	23.84	27.10	23.22
Services, other	24.9	19.8	---	17.04	17.77	24.24
Sum of six sectors	133.2	100.0	---	100.0	100.0	99.9

--- not applicable.
1. The shares in the lower half of column (1) are Domar weights.
2. Thousands, persons engaged in production (includes the self-employed).
3. Computer, communications equipment and semiconductor manufacturing; software publishing, information and data processing services, and computer systems design and related services.
4. Mining, manufacturing excl high-tech, utilities, and publishing (excl software).
5. Transportation, communications, and wholesale and retail trade.
6. Finance, insurance, real estate (except residential), and business and professional services.

In terms of productivity, the Domar weights in the bottom half of columns 1 indicate the impact that a percentage point increase in MFP in each sector will have on MFP for the aggregate economy. As may be seen, the industry and finance and business sectors have relatively large Domar weights.

Whether measured as sectoral output, deliveries to final demand, or value added, four large sectors: industry, distribution, finance and business, and other services sectors dominate U.S. business activity. Industry, which excludes high-tech manufacturing, is the largest sector in terms of gross output, sectoral output, and shipments to final demand, but it is the smallest of the four—by a wide margin—in terms of its employment share (and consequently it does not dominate in terms of value added share). The finance and business sector also is large for each of the metrics shown on the table. The remaining two sectors, high-tech and construction, are relatively small, but we isolate and study them separately owing to the key (but quite different) roles they play in the U.S. economic activity.

The sectoral decomposition of output and productivity (MFP) growth is shown in tables 5 and 6. Each **row** of table 5 is a sources-of-growth decomposition for each sector, with the first line in each block reporting the result for our "total" economy aggregate. As may be seen, aggregate sectoral output growth averaged 3.5 percent from 1987 to 2003, with the contributions from MFP, capital, labor, and imports from other sectors (including rest-of-world) playing a role. As may be seen, however, the sectoral sources-of-growth results vary noticeably with regard to the importance of MFP and the other factors. The accounting for intermediates through the use of sectoral output plays an important role in these results and in their analysis, even at the aggregate level. Imports of intermediate materials and some of the output of farms and government enterprises are inputs to production in the nonagricultural business sector and, on average, account for about 7 percent of aggregate sectoral output.

Each **column** of table 6 shows the sectoral decomposition of the contribution of each factor and MFP to aggregate growth. As may be seen, the pick up in MFP growth in the United States since 1995 was fairly broad-based, in that the high-tech, distribution, and finance and business sectors each contributed. The contribution of ICT capital also picked up fairly broadly among sectors, including, along with distribution and finance and business, the other services sector as well. Thus, although we view our results as still preliminary, they line up well with the analysis and conclusions of previous studies of the factors that contributed to productivity growth in the United States in recent years.

Nonetheless, the variability in the trend in MFP by sector is a striking result, and one we believe can be exploited for macro-forecasting and policy analysis. The trends by each sector are displayed more fully in the accompanying charts. For the aggregate and each sector we display both the trend in MFP estimated using the Hoddrick-Prescott filter and the step-up in the average growth rate of MFP since 1995. (We still have a few SIC-to-NAICS concordance issues, mainly in the series that compose the other services sub-aggregate, but as nearly as we can tell, the resolution of these issues would not change our basic results.)

5. Conclusion.

This paper introduces new estimates of sectoral and industry productivity using data classified according to NAICS from 1987 on. Our results illustrate that the six major sectors of the U.S. economy have very different trends in multifactor productivity growth. Although we have not yet performed formal forecasting experiments, our results strongly suggest that a separate accounting and forecasting of productivity in each of these sectors would assist in the estimation of the current trend in aggregate MFP. We plan to update the work reported in this paper to include more formal estimates of the trend and cycle components of MFP growth in each sector, an analysis of the cross correlations in MFP, and models of the evolution in the Domar sectoral weights.

We believe our framework has utility beyond our specific results and specific future plans. In attempting to understand productivity developments by "peeling back the layers of the onion," we suggest that modeling production at an intermediate level of aggregation—not just at the industry or at the aggregate level—may be the preferred way to go. High quality detailed data on industry output and inputs will always lag, but "intermediate" level results and trends could be estimated in real time.

Our approach also is desirable in that it involves using the concept of sectoral output, and we stressed that the two prevailing, seemingly different approaches to modeling production are joined by the use of sectoral output: One, at the industry level, models gross output and includes the use of intermediate inputs to allow for the possibility of substitution among all inputs (at this level gross output is essentially equal to sectoral output); the other, at the aggregate level, models value-added output (and at this level, too, sectoral output approaches value added). Of course, at the intermediate level, the concept of sectoral output is especially useful because it illuminates the role of "imported" intermediates in production and as well as the sector's role in supplying both to final demand and to other sectors.

An inherent advantage of approaching the study of productivity at an intermediate level of aggregation is that the effect of underlying economic mechanisms may be discerned. The sectors we studied were designed to highlight differences in production and MFP, but other limited aggregations of the underlying industry productivity estimates are possible. One could divide up the industries so that they reflect the cyclicality of final demand (i.e., industries that supply consumer durables, cyclical business equipment, exports, intermediates, and so on), the cyclical sensitivity of productivity, the level of innovative activity, the dependence on suppliers and purchased capital for technology, the competitiveness of markets, the average quality of labor input, the sensitivity to energy prices, etc.

Ultimately, however, the ability to create a system of flexible aggregation to isolate the various drivers of productivity for macroeconomic analysis depends on high quality data at the detailed industry level. We did not highlight the strengths and weaknesses of the data and data systems we are working with in this version of the paper, but we plan to incorporate a discussion of that topic in the final version.

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Table 5
Contribution to Sectoral Output Growth
Average Contribution, Ex-Ante Returns

	Domar Weight	Sectoral Output	TFP	Capital ICT	Capital EQX	Capital STR	Labor	Intmd.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. 1987-2003								
1. Private nonag. business		**3.5**	1.1	0.6	0.3	0.2	0.7	0.7
2. Excl. high-tech	97.0	3.0	0.6	0.5	0.3	0.2	0.7	0.7
3. Industry	40.5	1.3	0.8	0.2	0.1	0.0	-0.5	0.7
4. Construction	10.1	1.7	-0.3	0.1	0.1	0.0	0.6	1.2
5. Distribution	27.1	3.7	0.9	0.5	0.4	0.2	0.7	1.0
6. FIB	26.4	4.1	-0.6	0.9	0.8	0.2	1.2	1.5
7. Services	22.9	3.7	-0.3	0.4	0.2	0.2	1.3	1.9
8. High-Tech	7.3	12.2	6.8	0.7	0.2	0.1	0.1	4.3
B. 1987 to 1995								
1. Private nonag. business		3.1	0.8	0.4	0.4	0.2	0.7	0.6
2. Excl. high-tech	97.6	2.7	0.4	0.4	0.4	0.2	0.7	0.6
3. Industry	43.7	1.8	0.6	0.1	0.1	0.0	0.0	0.8
4. Construction	9.8	0.3	-0.3	0.1	0.0	0.0	0.5	0.0
5. Distribution	29.0	3.9	1.5	0.2	0.1	0.1	0.7	1.3
6. FIB	24.3	3.1	-1.2	0.7	1.1	0.4	1.0	1.1
7. Services	22.1	3.4	0.2	0.3	0.2	0.3	0.8	1.6
8. High-Tech	6.4	11.5	5.6	0.4	0.2	0.1	0.4	4.8
C. 1996 to 2003								
1. Private nonag. business		4.0	1.5	0.8	0.3	0.1	0.6	0.8
2. Excl. high-tech	96.4	3.4	0.9	0.7	0.3	0.1	0.6	0.8
3. Industry	37.2	0.9	1.0	0.2	0.1	0.1	-1.0	0.6
4. Construction	10.3	3.0	-0.3	0.1	0.2	0.0	0.6	2.3
5. Distribution	28.0	4.0	2.5	0.4	0.2	0.1	0.3	0.5
6. FIB	28.6	5.1	0.0	1.2	0.5	0.1	1.4	2.0
7. Services	23.6	3.9	-0.9	0.6	0.1	0.2	1.7	2.2
8. High-Tech	8.1	12.9	8.0	0.9	0.2	0.1	-0.2	3.9
D. Difference in Annual Averages, (1996 to 2003) vs. (1987 to 1994)								
1. Private nonag. business		**0.9**	$\boxed{0.7}$	0.3	-0.1	-0.1	-0.2	0.2
2. Excl. high-tech	-1.1	0.7	0.4	0.3	-0.1	-0.1	-0.1	0.2
3. Industry	-6.5	-0.9	0.4	0.1	0.0	0.0	-1.0	-0.3
4. Construction	0.4	2.8	0.0	0.1	0.2	0.0	0.2	2.3
5. Distribution	-1.0	0.1	1.0	0.2	0.1	0.0	-0.4	-0.8
6. FIB	4.3	1.9	1.1	0.4	-0.7	-0.3	0.4	0.9
7. Services	1.5	0.5	-1.1	0.3	0.0	-0.1	0.9	0.6
8. High-Tech	1.7	1.4	2.4	0.5	0.0	0.0	-0.7	-0.9

- For each row, column (2) equals the sum of columns (3) through (8).
- ICT is computers and peripherals, communication equipment, photocopy and related equipment, instruments, and software. EQX is other equipment, and STR is structures. Labor input is quality adjusted.

Table 6
Contribution to Sectoral Output Growth of Private Nonagribultural Business
Average Contribution, Ex-Ante Returns

	Domar Weight (1)	TFP (2)	Capital ICT (3)	Capital EQX (4)	Capital STR (5)	Labor (6)
A. 1987 to 2003						
1. Private nonag. business		1.1	0.6	0.3	0.2	0.7
2. Excl. high-tech	97.0	0.6	0.5	0.3	0.2	0.6
3. Industry	40.5	0.3	0.1	0.0	0.0	-0.2
4. Construction	10.1	0.0	0.1	0.0	0.0	0.1
5. Distribution	27.1	0.6	0.1	0.0	0.0	0.1
6. FIB	26.4	-0.1	0.3	0.2	0.1	0.3
7. Services	22.9	-0.1	0.1	0.0	0.1	0.3
8. High-Tech	7.3	0.5	0.1	0.0	0.0	0.0
B. 1987 to 1995						
1. Private nonag. business		0.8	0.4	0.4	0.2	0.7
2. Excl. high-tech	97.6	0.4	0.4	0.4	0.2	0.7
3. Industry	43.7	0.3	0.1	0.0	0.0	0.0
4. Construction	9.8	0.0	0.0	0.0	0.0	0.1
5. Distribution	29.0	0.4	0.1	0.0	0.0	0.2
6. FIB	24.3	-0.3	0.2	0.3	0.1	0.2
7. Services	22.1	0.1	0.1	0.0	0.1	0.2
8. High-Tech	6.4	0.4	0.0	0.0	0.0	0.0
C. 1996 to 2003						
1. Private nonag. business		1.5	0.8	0.3	0.1	0.6
2. Excl. high-tech	96.4	0.8	0.7	0.3	0.1	0.6
3. Industry	37.2	0.4	0.1	0.0	0.0	-0.4
4. Construction	10.3	0.0	0.0	0.0	0.0	0.1
5. Distribution	28.0	0.7	0.1	0.0	0.0	0.1
6. FIB	28.6	0.0	0.3	0.1	0.0	0.4
7. Services	23.6	-0.2	0.1	0.0	0.0	0.4
8. High-Tech	8.1	0.7	0.1	0.0	0.0	0.0
D. Difference in Annual Averages, (1996 to 2003) vs. (1987 to 1995)						
1. Private nonag. business		$\boxed{0.7}$	0.3	-0.1	-0.1	-0.2
2. Excl. high-tech	-1.1	0.4	0.3	-0.1	-0.1	-0.1
3. Industry	-6.5	0.1	0.0	0.0	0.0	-0.4
4. Construction	0.4	0.0	0.0	0.0	0.0	0.0
5. Distribution	-1.0	0.3	0.1	0.0	0.0	-0.1
6. FIB	4.3	0.3	0.2	-0.1	-0.1	0.1
7. Services	1.5	-0.3	0.1	0.0	0.0	0.2
8. High-Tech	1.7	0.3	0.0	0.0	0.0	0.0

- Up to rounding error, for each column, row (1) equals the sum of rows (3) through (8).

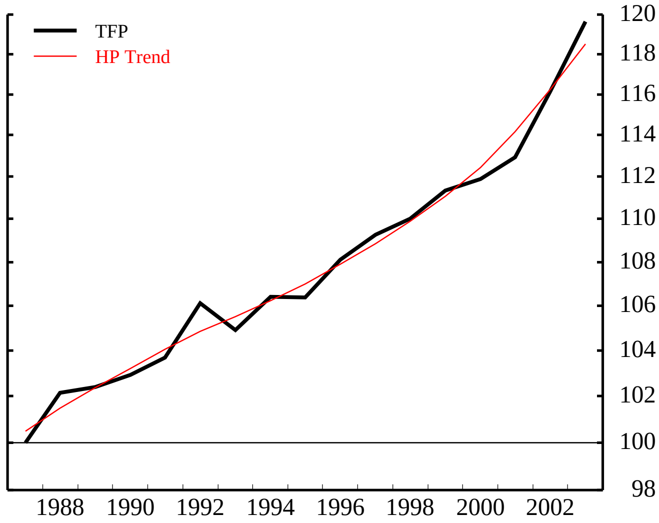
Table 7
Decomposing the Change in Aggregate Net Output Growth
Avg. Contribution in (1996 to 2003) less Avg. Contribution in (1987 to 1995)

	TFP (1)	Capital: ICT (3)	Capital: EQX (3)	Capital: STR (4)	Labor (5)
Within Sector Effect					
1. Private nonfarm business	0.66	0.31	-0.14	-0.09	-0.25
2. Industry	0.16	0.03	-0.01	0.01	-0.42
3. Construction	0.00	0.01	0.02	0.00	0.02
4. Distribution	0.28	0.06	0.03	-0.01	-0.11
5. FIB	0.29	0.11	-0.17	-0.08	0.11
6. Services	-0.25	0.07	-0.01	-0.01	0.20
7. High-Tech	0.18	0.03	0.00	0.00	-0.05
Between Sector Effect					
1. Private nonfarm business	0.01	0.04	0.03	0.01	0.10
2. Industry	-0.05	-0.01	-0.01	0.00	0.03
3. Construction	0.00	0.00	0.00	0.00	0.00
4. Distribution	-0.02	0.00	0.00	0.00	0.00
5. FIB	-0.03	0.04	0.03	0.01	0.05
6. Services	0.00	0.01	0.00	0.00	0.02
7. High-Tech	$\boxed{0.12}$	0.01	0.00	0.00	0.00

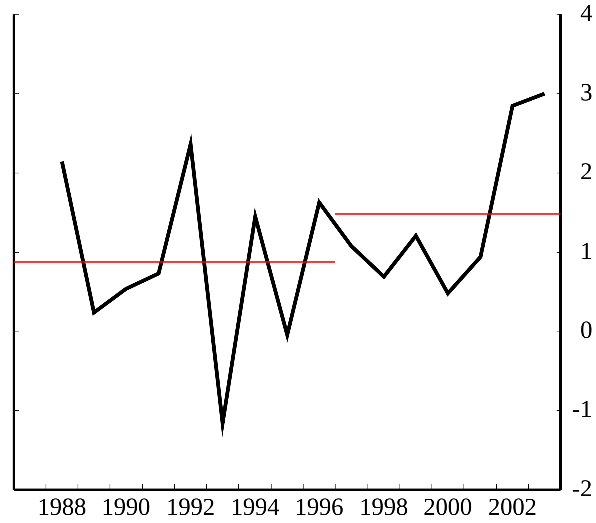
- Within sector effect calculated as the change in the growth rate of the factor input times the average domar weight.
- Between sector effect calculated as the change in the domar weights times the average growth rate in the factor input.
- Up to rounding error, for each column, row (1) equals the sum of rows (2) through (7).

Total Factor Productivity
Sectoral Output, Ex-Ante Returns

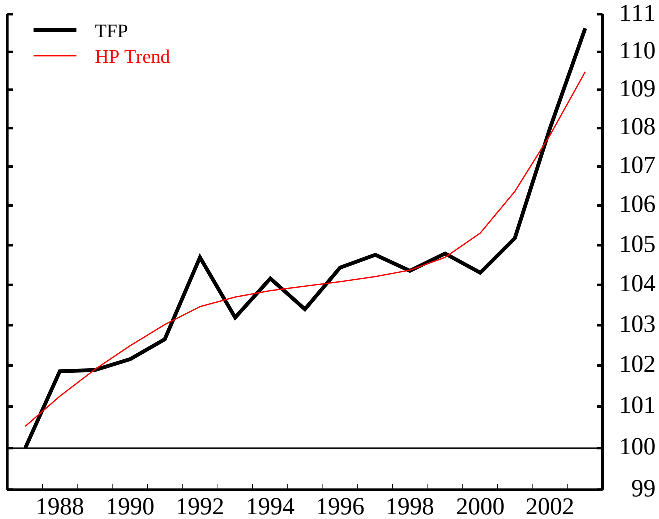
Private nonagricultural business
(1987=100)



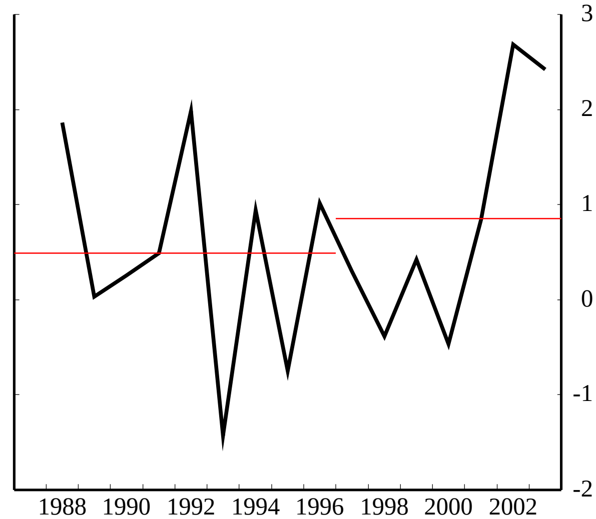
Private nonagricultural business
(Percent change)



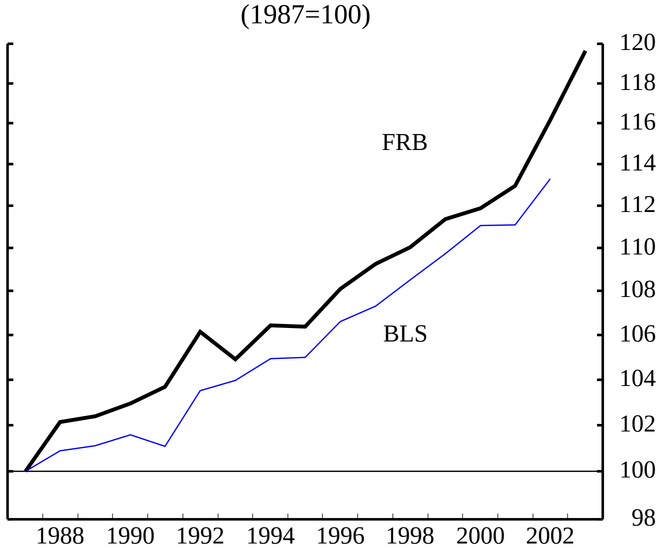
Private nonagricultural business, ex. high tech
(1987=100)



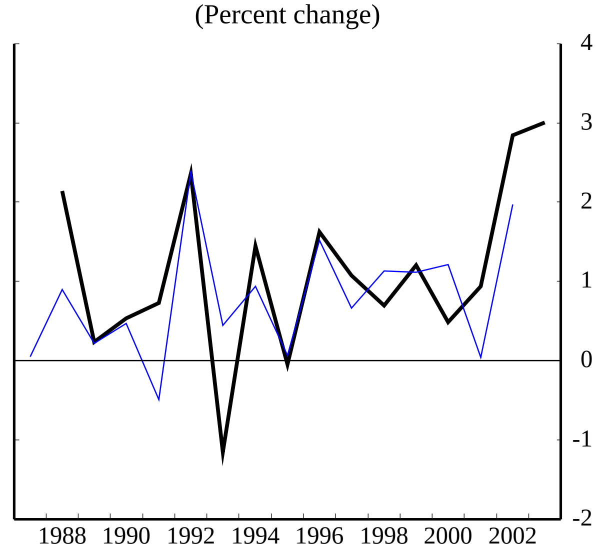
Private nonagricultural business, ex. high tech
(Percent change)



FRB vs. BLS
(1987=100)



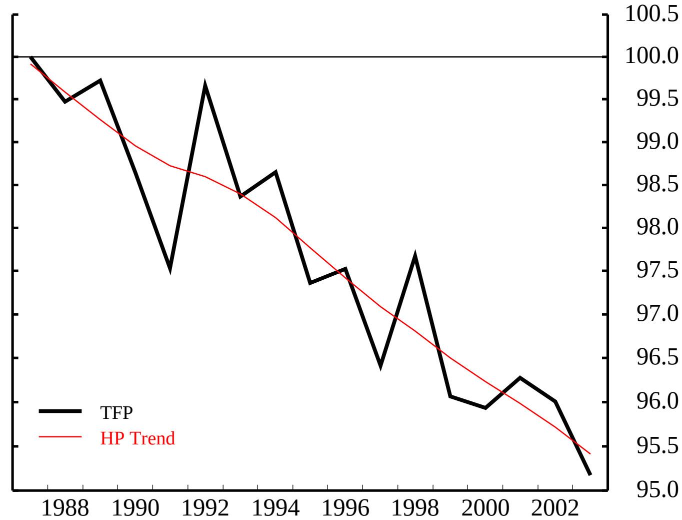
FRB vs. BLS
(Percent change)



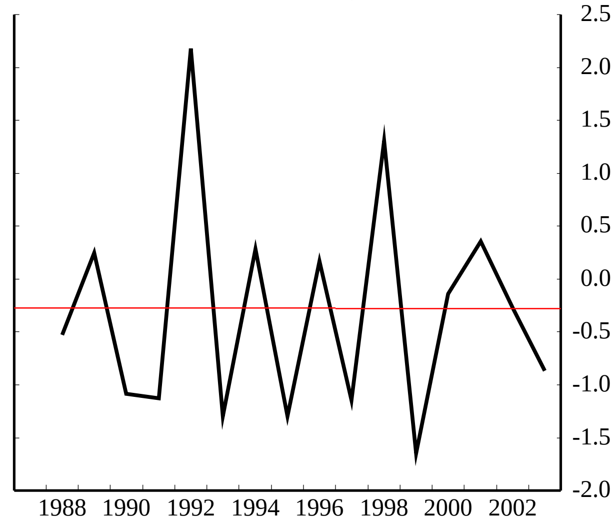
Note. BLS is Private Nonfarm Business.

Total Factor Productivity
Sectoral Output, Ex-Ante Returns

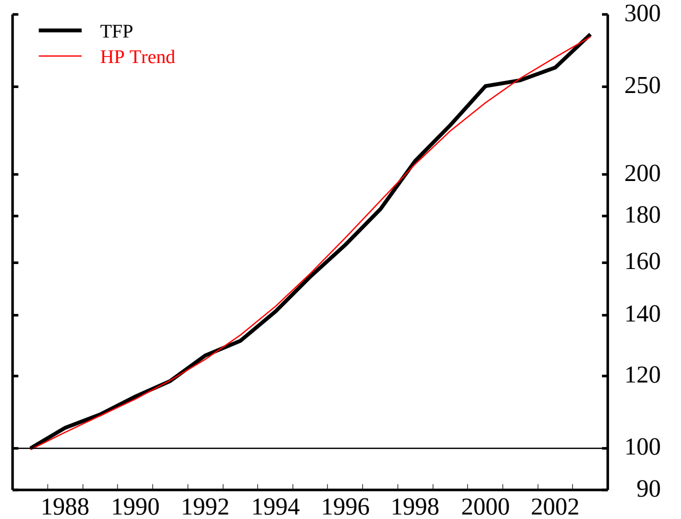
Construction
(1987=100)



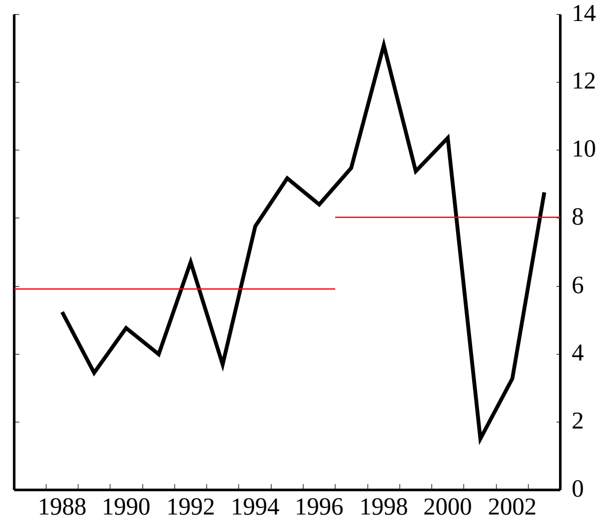
Construction
(Percent change)



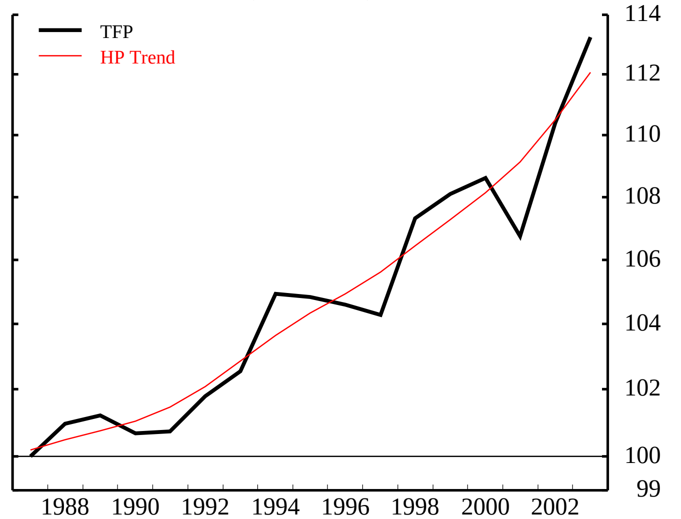
High tech
(1987=100)



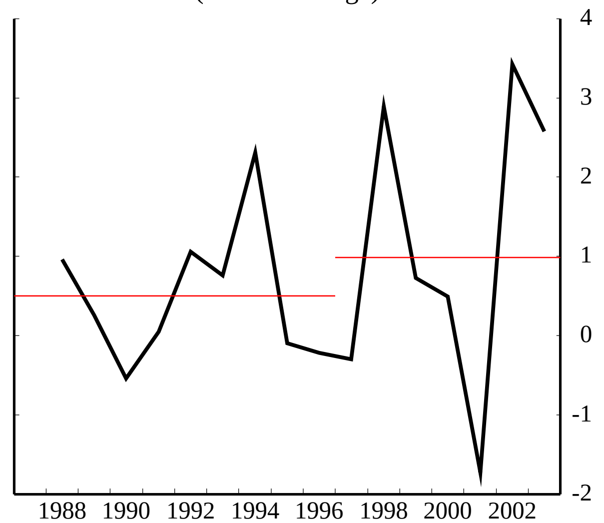
High tech
(Percent change)



Industry, ex. high tech
(1987=100)

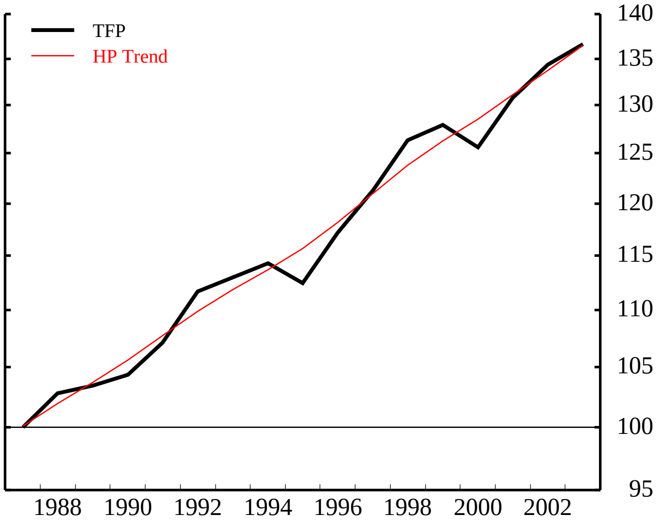


Industry, ex. high tech
(Percent change)

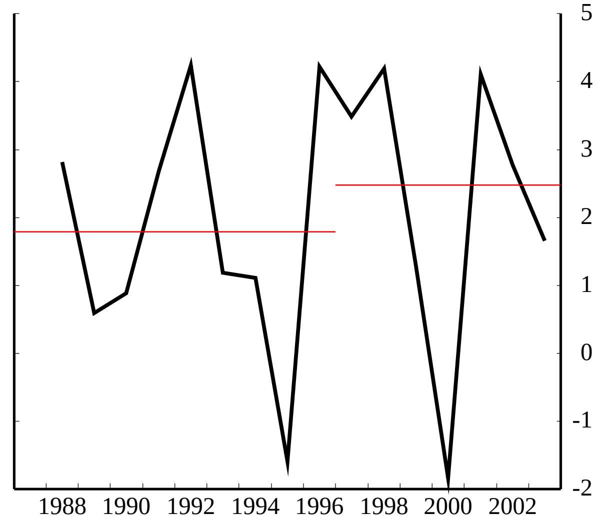


Total Factor Productivity
Sectoral Output, Ex-Ante Returns

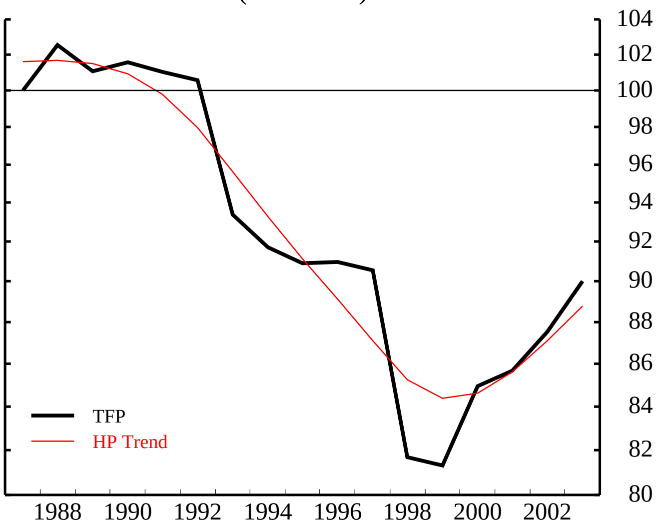
Distribution
(1987=100)



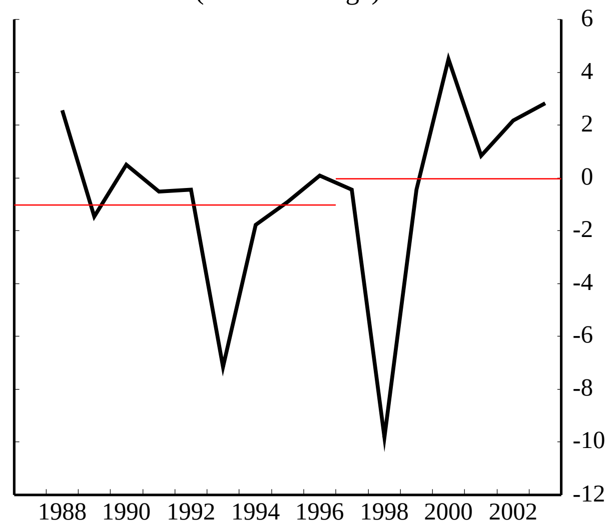
Distribution
(Percent change)



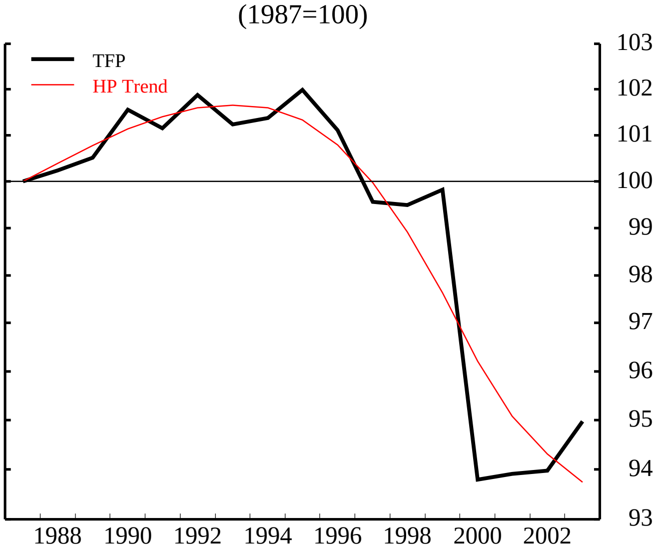
Finance and business
(1987=100)



Finance and business
(Percent change)



Services, other
(1987=100)



Services, other
(Percent change)