FEDERAL RESERVE BANK OF ST. LOUIS

REVIEW

MARCH/APRIL 2002 | VOLUME 84, NUMBER 2

Review is published six times per year by the Research Division of the Federal Reserve Bank of St. Louis. Single-copy subscriptions are available free of charge. Send requests to: Federal Reserve Bank of St. Louis, Public Affairs Department, P.O. Box 442, St. Louis, MO 63166-0442, or call (314) 444-8808 or 8809.

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can be called the “policy innovation paradox” because there is no obvious explanation for such a pattern. This article shows that the policy innovation paradox is most likely an artifact of failing to account for the discreteness of changes that policymakers make to the target federal funds rate. Mis-specified VARs that fail to account for discrete target changes imply the policy innovation paradox, whereas a model that uses information from discrete policy changes does not.

Eulogy for Darryl R. Francis, 1912-2002

Former President and CEO, Federal Reserve Bank of St. Louis

by William Poole, President and CEO,
Federal Reserve Bank of St. Louis
February 12, 2002

We are here today to celebrate a life well led. I am honored that Darryl's widow, Sherrian, asked me to speak this morning.

I came to know Darryl Francis personally just a bit in the final years of his life, after I moved to St. Louis four years ago. But long before then, I knew him very well by reputation, through many economists who worked at the St. Louis Fed during his tenure. As a consequence of my close tracking of monetary policy debates starting in the 1960s, I came to appreciate how extremely important Darryl was in this nation's monetary history.

Darryl was president of the Federal Reserve Bank of St. Louis from 1966 to 1976. To understand the importance of his role, I need to recount just a bit of the economic history of that period. Inflation began to rise in 1965, and year by year became an increasingly difficult problem for the United States until 1982. As president of the Bank, Darryl sat on the Federal Reserve's principal monetary policy body, the Federal Open Market Committee. Over the years of his membership on the FOMC, his position was consistent and stated often with quiet eloquence. The issue was simple: to end the inflation, the Federal Reserve needed to slow the rate of money creation. Controlling money growth was and is the Fed's responsibility; no private party, no other organization can do it.

The FOMC did slow money growth in 1966, but not for long. Money growth and inflation rose in 1967. Subsequent policy tightenings in 1969 and 1973-74 were in each case followed by periods of excessive money growth. Inflation rose and became ever more intractable. In FOMC meetings, Darryl Francis spoke again and again against inflation and the money growth that was causing it. I know that personally because I've read the minutes of the FOMC for that period.

But Darryl did much more than speak against inflation and excessive money growth at FOMC meetings. With his research director, Homer Jones, he built a research division of first rank and encouraged research on the inflation issue. Francis, Jones, and the research economists were convinced that the analysis of the Chicago School of monetary economics, led by Milton Friedman, held the key to the inflation problem. Money growth had to be restrained, and consistently restrained over the long run.

The Chicago view is mainstream economics today, but it wasn't at that time. Darryl brought this analysis into the Federal Reserve System. More importantly, he brought the analysis to the general public through his speeches and argued the case to professional audiences through scholarly papers published by the Bank's research economists.

In speaking out, Darryl Francis took a public stance that required great courage. In plain terms, he said that the organization he worked for was responsible for creating and maintaining inflation. That was not a popular position at the Fed's Board of Governors in Washington, and I know that a lot of pressure was applied to try to get Darryl to be quiet. A great strength of the Federal Reserve System is that the 12 regional Federal Reserve Banks have substantial independence. Darryl Francis used that independence for this great cause of ending the scourge of inflation. He helped shape the public debate. The policies he advocated were not adopted during his term of office, but later they were the basis of the policies pursued by Paul Volcker, when he became Fed Chairman in 1979. These policies were understood by Ronald Reagan, without whose support Volcker could not have stood the course through the 1981-82 recession, at the time and still the most serious U.S. recession since the Great Depression.

Darryl's courage in addressing the inflation problem did more than contribute to solving it. His example inspired the work of the St. Louis Fed economists and led the entire Federal Reserve System to become a much more open organization. St. Louis came to be regarded as something of a maverick among Reserve Banks, and the Federal Reserve Bank of St. Louis came to be known, and still is known, I believe, as the premier Fed bank in economics research.

I met Darryl once or twice while he was St. Louis Fed president. One vivid memory of mine was while I was a junior staff member at the Board of Governors in the early 1970s. An occasional junior staff member was permitted to attend an FOMC meeting, and I got to go once. I don't remember now which meeting it was, but I do remember watching and listening to Darryl at that meeting. His was a lonely voice at that FOMC meeting. As I confirmed later when reading the FOMC minutes of the period, he rarely had other FOMC members who shared his views. But he was right, and the world eventually saw that he was right.

In recent years I got to know Darryl just a bit. I was especially pleased that he and Sherrian could attend the Bank's annual research conference in October 2000. We dedicated that conference to him in recognition of his great contribution to the Bank and to the nation.

As I've said before, and will say again, Darryl is a hero of mine.

I'll repeat a story one of his friends told me. During his active years, Darryl had many hobbies, each of which he pursued with considerable energy and intensity. At the time he retired from the St. Louis Fed and moved to Fort Smith, one of those hobbies was collecting wine. He had accumulated a substantial wine cellar, which the moving company refused to move. So, Darryl had to make quite a few trips in his station wagon to transport his wine collection. Given that these trips had to be squeezed between other work, at the end of the process he was all but exhausted from the many drives to Fort Smith and back to St. Louis. He ended up with some knee problems, which took quite some months to clear up. In telling me the story, Darryl's friend chuckled and said that the knee problems were surely just retribution for moving all that wine to Arkansas, which was a lot dryer state in the mid 1970s than it is today.

Gene Leonard is a person who knew Darryl for many years, and he regrets he could not be here today. Gene served under Darryl in several positions including as the First Vice President of the Federal Reserve Bank of St. Louis. Gene sent me a few words that I'll read.

> Darryl Francis was my boss for 15 years. He was also my mentor, a father figure, and a close friend. Ironically we met at a funeral, as pallbearers for a professor at the University of Missouri we had had in common a generation apart, and to whom we had each become quite close. A job offer followed, and a relationship began.
>
> Darryl was the best boss a person could ever hope for. We wanted to work hard as much to please Darryl and make him proud as for our own paycheck. He didn't have the "ego problem" that characterizes many CEOs. He led by inspiration, not by intimidation.
>
> At the end of the working day, Darryl left the problems of the banking world and the economy at the door of his office, making time to indulge with a passion whatever hobby or interest he was pursuing at the time. We learned not to be overly consumed by our jobs—one's success was not enhanced by being the first to arrive and the last to leave. "Don't you have a family?" he would ask. The privilege of working for him was an important part of our compensation.
>
> Darryl had a wonderful sense of humor—sometimes we would laugh together till tears came to our eyes. His verbal expressions reflected his North Missouri rural upbringing, and his wisdom. Once when a colleague made an embarrassing mistake, Darryl said: "He kinda tore his pants a little goin' over the fence." I never forgot that because I had done it myself—literally and figuratively. Darryl led a long and productive life—a good life. Let us be grateful for that. I miss him already.

Gene, I miss him too. Darryl will remain a hero to me and we'll all miss him. Now Darryl will go to his final resting place. He was preceded in death by his beloved first wife of 58 years, Loretta France Smyth, and will be buried alongside her here in Fort Smith.

The High-Tech Investment Boom and Economic Growth in the 1990s: Accounting for Quality

Michael R. Pakko

Purchases of computers, software, and communications equipment grew rapidly during the 1990s, representing an increasing share of total U.S. investment spending over the course of the decade. Using official statistics from the U.S. Bureau of Economic Analysis (BEA), nominal investment expenditures for three categories—computers and peripheral equipment, software, and communications equipment—rose to account for over one-third of total business fixed investment by the year 2000, up from only one-fifth a decade earlier. In real, price-adjusted terms, the dramatic rise in spending on these information and communications technologies (ICT) has been even more pronounced: the ratio of real ICT expenditures to real business fixed investment rose from about 15 percent in 1990 to nearly 50 percent in 2000.[1]

This surge in ICT spending was, in turn, a notable feature of the investment boom and rapid economic growth of the late 1990s. From 1995 through 2000, business fixed investment accounted for nearly 32 percent of the total growth of real gross domestic product (GDP). In contrast, investment spending had accounted for only 15 percent of growth during the 1970s and 1980s.

One factor that is potentially important for interpreting the rapid growth of ICT spending in the 1990s is the use of improved methods for measuring quality change, particularly for components of ICT investment spending. As a result of these quality adjustments, the growth rate of reported ICT spending is much higher than the growth rate of the number of unit sales. This is entirely appropriate. A typical personal computer purchased in 2002, for example, is clearly not directly comparable to one purchased a decade ago without some adjustment for advances in the computing power of newer models.

In addition to computers and peripheral equipment, the BEA explicitly accounts for quality improvement in calculating the growth rates of some components of computer software and for telephone switching equipment.[2] Hence, in calculating the measured real growth rate of ICT investment spending, official statistics are carefully constructed to account for quality improvement.

The fact that ongoing quality improvement is explicitly measured for these ICT sectors—but not so for many other components of investment spending—raises the question of whether the quality adjustment itself might be responsible for the observed prominence of high-tech investment during the 1990s: Is the higher economic growth associated with high-tech investment an artifact of the methodology used to construct recent data, or does it truly represent a departure from the past?[3]

One way to address this question would be to consider adjusted measures of investment that abstract from quality change in the ICT components. However, given the evident recent advances in computing and communications technologies, quality adjustment for these categories is clearly appropriate. Using fixed prices to evaluate growth in the ICT sectors would drastically understate true economic growth. An alternative approach to evaluating the role of quality improvement would be to adjust non-ICT investment data for quality improvement that might not be reflected in the official statistics, creating aggregate measures of investment that account for quality improvements across the board.

This paper undertakes such an exercise. Specifically, I extrapolate data from Gordon's (1990) detailed study, *The Measurement of Durable Goods Prices*, to

Michael R. Pakko is a senior economist at the Federal Reserve Bank of St Louis. Rachel Mandal provided research assistance.

[1] The ICT measures used in this paper include the categories of computers and peripheral equipment, software, and communication equipment. These are three of the six categories that comprise the set of investment goods known as information processing equipment and software. The three remaining elements of this measure are instruments, photocopy and related equipment, and office and accounting equipment.

[2] See Landefeld and Grimm (2000) and Landefeld and Fraumeni (2001).

[3] Landefeld and Grimm (2000) examine this question as well. Citing the consistency with which quality-adjustment measures have been applied to ICT investment categories, they suggest that the measurement of quality has not, in fact, distorted measures of investment spending. This article goes further to investigate the role of quality change by incorporating sources of quality improvement that are unmeasured in other categories of investment.

Table 1

Output and Investment: Growth Rates and Contributions of Investment to GDP Growth for NIPA Data

	50s	60s	70s	80s	90s	95-00
Growth rates						
GDP	3.53	4.19	3.23	3.21	3.25	4.11
Nonresidential fixed investment	3.04	6.52	5.45	3.40	7.84	10.58
Structures	4.15	4.47	3.46	0.84	1.65	5.43
Equipment and software	2.41	7.80	6.63	4.88	10.19	12.37
IP equipment and software	9.04	14.96	15.37	11.63	16.44	20.60
ICT	14.34	20.04	17.48	14.45	19.63	24.51
Contribution to GDP growth Percentage points (percent of GDP growth)						
GDP	3.53	4.19	3.23	3.21	3.25	4.11
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)
Nonresidential fixed investment	0.27	0.62	0.58	0.39	0.88	1.25
	(7.58)	(14.82)	(18.12)	(12.15)	(27.11)	(30.37)
Structures	0.15	0.16	0.13	0.03	0.04	0.16
	(4.12)	(3.85)	(4.14)	(0.78)	(1.25)	(3.89)
Equipment and software	0.12	0.46	0.45	0.36	0.84	1.09
	(3.46)	(10.97)	(13.98)	(11.36)	(25.84)	(26.44)
IP equipment and software	0.06	0.17	0.27	0.32	0.58	0.78
	(1.74)	(4.04)	(8.44)	(10.10)	(17.77)	(18.90)
ICT	0.04	0.14	0.21	0.30	0.55	0.75
	(1.18)	(3.33)	(6.42)	(9.26)	(16.98)	(18.38)

construct a quality-adjusted measure of nonresidential fixed investment in equipment and software (NFI-E&S). I also apply a long-term estimate of quality improvement for nonresidential structures calculated by Gort, Greenwood, and Rupert (1999) to create an adjusted aggregate for total nonresidential fixed investment (NFI).[4] A comparison of these data with the official measures reported in the national income and product accounts (NIPA) provides a way to evaluate the importance of this measurement issue in evaluating the contribution of high-tech investment spending to recent trends in investment and overall economic growth.

TRENDS IN INVESTMENT AND GROWTH

It has been widely noted that the strength of the U.S. economy in the late 1990s was largely attributable to a boom in investment spending, particularly for high-technology goods. Table 1 illustrates the significance of investment spending in the 1990s, detailing the contribution of high-tech investment growth to the growth rate of real GDP in comparison with previous decades.[5] At each level of aggregation, the 1990s stand out as a decade in which investment spending figured prominently in the composition of economic growth. Total nonresidential fixed investment expanded at a rate of 7.8 percent, accounting for nearly a full percentage point of GDP growth over the decade. In contrast, investment growth was only 4.6 percent over the previous four decades, accounting for less than one-half of 1 percent of GDP growth.

The growth rate of equipment and software investment rose to 10.2 percent in the 1990s (up from an average of 5.4 percent in the previous four

[4] The quality-adjusted data set constructed for this article is available at < www.stls.frb.org/publications/review > .

[5] Contributions to growth reported in this article are averages of annual rates, calculated using the formula used by the BEA—see Moulton and Seskin (1999). An alternative formula for calculating approximate growth contributions over a multi-year horizon is presented in Landefeld and Parker (1997).

Table 2

Components of Equipment and Software Investment: Growth Rates and Contributions to E&S Growth for NIPA Data

	50s	60s	70s	80s	90s	95-00
Growth rates						
Total E&S growth	2.41	7.80	6.63	4.88	10.19	12.37
IP equipment and software	9.04	14.96	15.37	11.63	16.44	20.60
ICT	14.34	20.04	17.48	14.45	19.63	24.51
Industrial equipment	3.32	6.04	3.08	0.38	4.62	4.64
Transportation equipment	1.79	6.60	5.04	1.60	8.20	8.28
Other equipment	1.05	6.43	4.12	1.33	4.12	5.67
Contribution to E&S growth Percentage points (percent of E&S growth)						
Total E&S growth	2.41	7.80	6.63	4.88	10.19	12.37
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)
IP equipment and software	1.09	2.78	3.74	4.25	6.96	8.80
	(45.26)	(35.59)	(56.43)	(87.21)	(68.31)	(71.16)
ICT	0.74	2.28	2.81	3.89	6.63	8.56
	(30.86)	(29.30)	(42.41)	(79.85)	(65.10)	(69.23)
Industrial equipment	0.89	1.75	0.75	0.02	0.90	0.87
	(36.82)	(22.40)	(11.30)	(0.33)	(8.85)	(7.02)
Transportation equipment	0.19	1.75	1.25	0.30	1.66	1.72
	(7.83)	(22.46)	(18.93)	(6.16)	(16.31)	(13.92)
Other equipment	0.28	1.61	1.01	0.20	0.70	1.00
	(11.47)	(20.59)	(15.28)	(4.18)	(6.86)	(8.08)

decades) and accounted for over 95 percent of the contribution of total investment to GDP growth. Two-thirds of that contribution was attributable to ICT investment. Note that although the growth rate of ICT spending was consistently high over the entire 50-year period—averaging over 17 percent—its contribution to total economic growth has become notable only in recent years as high-tech spending has comprised a larger share of total investment. In the 1960s, a 20 percent growth rate of ICT spending contributed only 0.14 percent to GDP growth; in the 1990s a similar growth rate contributed 0.55 percent.

This feature is also evident in the data presented in Table 2, which details the growth rates of the main subcomponents of equipment and software investment. Table 2 also reveals—somewhat contrary to conventional wisdom—that the importance of the ICT component of equipment investment dates back much earlier than the boom of the past decade. As far back as the 1950s, information processing equipment and software accounted for well over one-third of the growth in total equipment and software purchases, exceeding the contributions of each of the other components: industrial equipment, transportation equipment, and other equipment.

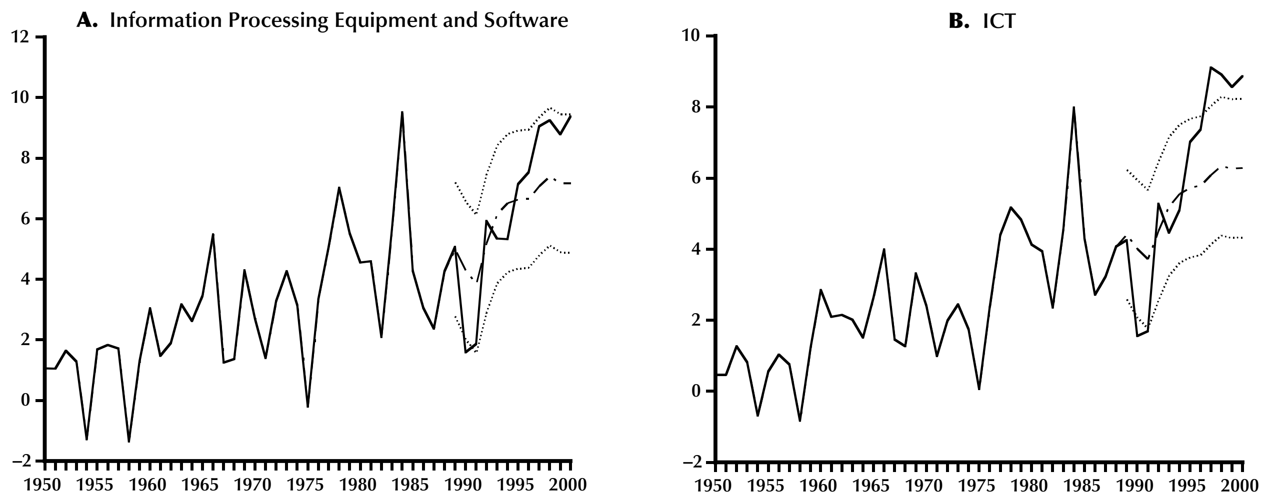
In the 1980s, despite a slowdown in growth, information processing equipment and software accounted for nearly 90 percent of the growth in total equipment and software spending. In large part, this is attributable to an even sharper slowdown in the growth rates of the other components. The investment boom of the 1990s is associated with a rebound of growth in all categories of equipment and software investment, but with the share of the information processing and software component having risen to the point that its growth contribution overwhelmed the increases in other categories.

The last columns in Tables 1 and 2 show that these trends were even more pronounced in the latter half of the decade. For example, total spending on equipment and software accelerated to a growth

Figure 1

Contributions to Growth of Equipment and Software Investment

NIPA Data and Forecasts



rate of 12.4 percent, accounting for more than one-fourth of total GDP growth. ICT spending growth rose to nearly 25 percent, accounting for over two-thirds of the growth in total equipment and software spending.

HOW DIFFERENT WERE THE 1990s?

Clearly, ICT spending, and investment spending more generally, accelerated in the 1990s, accounting for increasing shares of overall economic growth. However, the rising prominence of these components also reflected trends that were evident well before the boom of the last decade. An important question therefore remains: Did the acceleration of the 1990s represent an unusual or exceptional period, or was it simply a continuation of the longer-term evolution of the structure of the U.S. economy?

To address this question, I estimate a set of simple time-series models for the growth contributions of various investment components, using data through 1988. The models are then used to forecast the 1990s, providing a means for evaluating actual growth relative to what might reasonably have been expected ex ante.

The variables to be modeled and forecasted are the growth contributions of investment components to the growth rate of a broader aggregate—either total NFI-E&S or total GDP—as summarized in the lower panels of Tables 1 and 2. In each case, the growth component is regressed on its own lagged value, a constant, and a time trend.[6] Cyclical characteristics of the series are modeled by including in the regression the current growth rate of the aggregate to which the growth contribution refers (NFI-E&S or GDP).

To adjust for problems associated with simultaneous equation bias, the models are estimated with two-staged least squares, using instrumental variables for the aggregate growth rates.[7] The instruments used are growth rates for subaggregates that include everything in the total aggregate *except* the component being modeled.[8]

Figure 1 shows the contribution of high-tech investment components to total NFI-E&S growth, along with the forecast for the 1990s from the time-series models. Panel A focuses on the information processing and software component. The actual growth contribution of this component during the late 1990s exceeded the growth rate forecasted by the model (shown by the dashed line). For 1996-2000, the contribution of information processing

[6] Although the constant and time trend were not significant in all the regressions, both were included in all cases to maintain consistency.

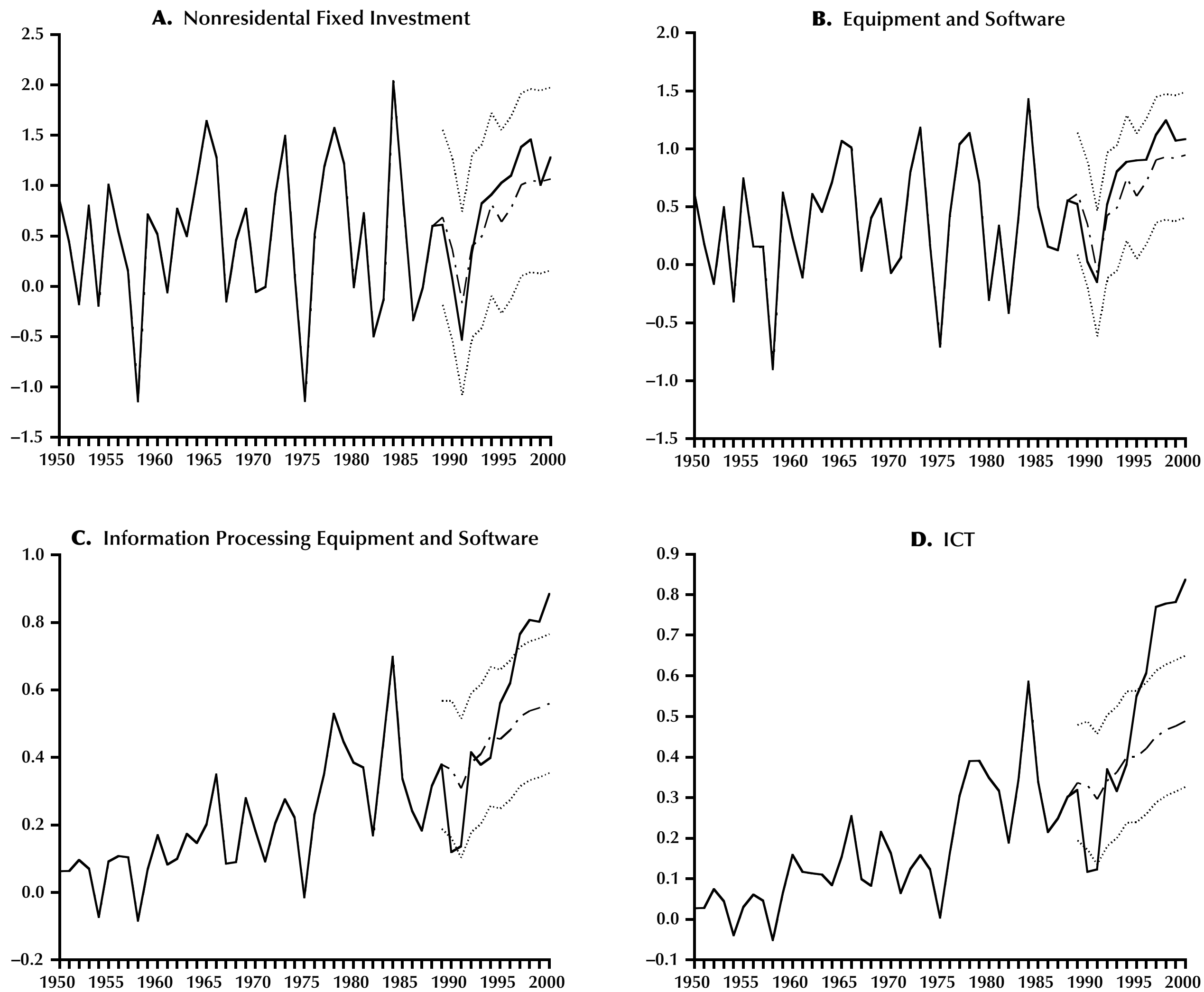
[7] Simultaneous equation bias arises because the growth contribution being estimated and forecasted is, by definition, a component of the aggregate growth rate used to capture cyclical behavior on the right-hand side of the equation. Consequently, these regressors are likely to be correlated with the error term of the estimation equation.

[8] These subaggregates are constructed by "unchaining" the featured component from the aggregate—that is, by a chain-weighted subtraction.

Figure 2

Contributions of Growth of GDP

NIPA Data and Forecasts



equipment and software to NFI-E&S averaged 1.7 percentage points more than predicted by the model. Nevertheless, the actual growth contribution remains within the bounds of a confidence interval (dotted lines) representing ± 2 times the standard errors of the forecast. That is, although information processing equipment and software contributed more to NFI growth in 1996-2000 than would have been predicted by the model, the deviation from expectations is not statistically significant.

Panel B of Figure 1 shows the contribution of ICT investment to equipment and software growth. In this case the actual growth contribution greatly exceeds the forecast in the latter half of the 1990s, surpassing the simulated path by an average of 2.4 percent annually during the 1996-2000 period, and moving outside the confidence interval during that period as well. In this sense at least, the ICT investment boom in the late 1990s did represent a significant departure from the past in terms of the composition of total investment spending.

For each of the measures considered in Figure 1, it is interesting to note that the sharp downturn in high-tech investment growth in the early 1990s slightly exceeds the lower confidence bound for the forecasts. The contribution of high-tech investment to overall fixed investment growth was evidently more variable over the most recent business cycle than would have been anticipated from past experience.

Figure 2 shows the actual and forecasted contributions of investment growth—at various levels of disaggregation—to the growth rate of total GDP. The growth contributions of total nonresesidental fixed investment and of equipment and software, shown in panels A and B, respectively, fall slightly below their forecasted values early in the 1990s and are higher than expected throughout the remainder of the decade. From 1996-2000, the actual contributions of these measures to total GDP growth exceeded their forecasted values by 0.25 percent and 0.20 percent, respectively. However, neither investment measure strays far enough away from its forecasted path to move outside its confidence interval.

For more narrow measures of investment focusing on high-tech capital goods, the actual contributions to GDP growth deviated significantly from previous patterns. The contributions of information processing equipment and software and of ICT spending—shown in panels C and D, respectively—contributed more to both the downturn of the early 1990s and the boom of the late 1990s than previous trends and fluctuations would have suggested. The contribution of ICT growth to GDP growth, in particular, greatly exceeds the upper confidence bound during 1996-2000.

The time-series analyses illustrated in Figures 1 and 2 suggest that, although the contribution of investment to overall economic growth in the 1990s did rise relative to past growth trends, the deviations are significant only for narrower measures of high-tech investment spending. Because it is the quality-adjusted growth contributions of the ICT sectors in particular that significantly accelerated in the late 1990s, the issue of unmeasured quality change in the other components of investment spending takes on a potentially crucial role in assessing the true importance of high-tech investment spending in the evaluation of recent growth trends.

MEASURING QUALITY CHANGE

The measurement of quality change has always been important in the construction of the NIPA data. Quality characteristics of newly introduced goods are routinely incorporated into the data using so-called "matching models" that compare the attributes of new and existing products. In recent years, the BEA has implemented several revisions to its methodologies in order to account for the rapid rate of innovation in ICT and other high-tech sectors. In particular, so-called "hedonic regression techniques" have been applied to construct quantity and price indices that adjust for changes in quality over time. (See insert, "Measuring Quality Improvement with Hedonics.") Among the more important applications of this approach, the BEA incorporates hedonic indices for computer equipment and purchased software, telephone switching equipment, cellular services, and video players, among others.[9] Moreover, the BEA has even changed its aggregation methodology to more accurately measure the contribution of quality change to GDP growth: the adoption in 1996 of a chain-weighting methodology was intended to allow aggregates to track quality improvement better over time.

Nevertheless, some economists contend that a significant amount of quality change goes unmeasured in the official statistics, particularly in cases where quality improvement is more incremental. As detailed in his 1990 book, *The Measurement of Durable Goods Prices*, Robert Gordon undertook to quantify the extent of this unmeasured quality change. Drawing data from a variety of sources, including special industry studies, *Consumer Reports*, and the Sears catalog, Gordon compiled a data set of more than 25,000 price observations. Using a number of methodologies—including traditional matching methods, hedonic price index construction, and price comparisons for used capital equipment—he compiled the data into quality-adjusted price indexes for 105 different product categories, then aggregated the data to correspond to the individual components of the BEA's measure of spending on producers' durable equipment. In particular, he calculated "drift ratios," representing the difference between the growth rates of his quality-adjusted price data and the official NIPA price indexes, then aggregated the components to create a new quality-adjusted real investment series.

Table 3 shows long-run averages of Gordon's drift ratios for individual components of investment spending. The table is organized by the contemporary categories and definitions for private NFI-E&S, which differs somewhat from the taxonomy used at the time that Gordon compiled his data. The growth rates in Table 3 represent the spreads between the official growth rates and the growth rates of Gordon's

[9] Landefeld and Grimm (2000) report that 18 percent of GDP is estimated using hedonic methods.

MEASURING QUALITY IMPROVEMENT WITH HEDONICS

As quality improvement in high-tech goods has become increasingly evident, a technique known as "hedonic regression" has been incorporated in the measurement of several categories in the national accounts. A hedonic price index—so named because it attempts to measure the quantity of utility, or pleasure, derived from a particular good—is a statistical technique that adjusts the price of an item to reflect improvements in quality. For example, a personal computer purchased in 2002 might cost the same amount as one purchased a decade earlier, but the newer model is clearly superior in terms of overall computing power.

The hedonic regression approach to quantifying this type of comparison is not a particularly new idea: one of its earliest applications was to the comparison of automobile quality across model years in the 1930s.[1] It is particularly well-suited to compare goods that can be thought of as comprising a bundle of underlying attributes, each of which is assumed to have its own intrinsic value.

In the case of personal computers, the components inside the "box" itself have several independent, measurable attributes (e.g., processor speed, memory, disk storage capacity). The hedonic approach estimates the value of these attributes by constructing a regression model relating the prices of computers to data on their underlying attributes.

The value of new computers can be expressed relative to the vintage computers by using values predicted by estimated model parameters. That is, the ratio of nominal expenditures on new computers to their model-predicted prices yields a measure of the real computing power of the new model relative to the older models. Unit production or sales figures for the number of "boxes" would fail to capture this adjustment.

The effect of this methodology on measured quantities and prices can be dramatic. From 1987 to 2000, the ratio of the quality-adjusted price index for final sales of computers and peripheral equipment to the price index for non-computer final sales declined nearly 95 percent. That is, the quantity of computing power purchased with one dollar in 1987 would cost only a nickel by the year 2000, after accounting for both quality improvement and inflation.

1 Triplett (1986) attributes the origin of hedonics terminology to Court (1939).

quality-adjusted measures. Over the span of the entire sample period, 1947-83, the drift ratios are uniformly positive, indicating unmeasured quality improvement.[10] In many cases, the magnitude of the quality adjustment is remarkable. Not surprisingly, Gordon's estimates of unmeasured quality improvement are particularly large for the high-tech categories of computing and communications equipment (prior to the adoption by the BEA of hedonic methodologies for these categories). Drift ratios for some components of transportation equipment, particularly aircraft, also indicate substantial undermeasurement of quality change over the sample period.

Generally, the magnitudes of the drift ratios are smaller in the later years of the sample period.[11] This observation is consistent with the hypothesis that the official statistics more accurately measure quality change in the 1970s and 1980s than they did in earlier decades.

The bottom line of Gordon's study was that the official NIPA data understated the true growth rate of investment spending by nearly 3 percentage points over the period 1947-83. The importance of this finding for evaluating recent investment and economic growth is twofold: First, if unmeasured quality improvement caused investment to be understated in the past, more recent growth trends—which do account for a great deal of quality change—might not be so extraordinary after all. In addition, accounting for possible unmeasured quality improvement in the non-ICT components of investment spending should have the effect of diluting the contribution

10 The signs of the drift ratios reported in Table 3 are reversed from those reported in the summary tables in Gordon's book, which report the adjustment to prices rather than quantities.

11 In some cases, the drift ratios are even negative for the 1973-83 period, indicating that the official data capture more quality improvement than is revealed by Gordon's calculations.

Table 3

Drift in the Ratio of Official to Alternative Deflators for Components of Private Nonresidential Fixed Investment in Equipment and Software

	Growth rates (percent)	
	1947-83	1973-83
Information processing equipment and software		
Computers and peripheral equipment*	15.33	7.37
Software†	NA	NA
Communication equipment	6.42	8.13
Instruments‡,§	3.50	2.99
Photocopy and related equipment‡,§	3.50	2.99
Office and accounting equipment¶	6.80	6.82
Industrial equipment		
Fabricated metal products	1.78	–0.42
Engines and turbines	3.50	0.47
Metalworking machinery	1.15	0.96
Special industry machinery, n.e.c.‡	2.47	2.81
General industrial, including materials handling, equipment	1.79	1.25
Electrical transmission, distribution, and industrial apparatus	2.09	0.40
Transportation equipment		
Trucks, buses, and truck trailers‡	3.00	0.56
Autos	1.35	–2.07
Aircraft	8.29	3.65
Ships and boats‡	1.93	1.39
Railroad equipment	1.47	1.78
Other equipment		
Furniture and fixtures	1.44	0.53
Tractors	1.41	3.17
Agricultural machinery, except tractors	0.68	–0.19
Construction machinery, except tractors	1.62	0.68
Mining and oilfield machinery‡	1.62	0.68
Service industry machinery	3.15	3.64
Electrical equipment, n.e.c.	1.08	0.18
Other‡	1.98	1.68

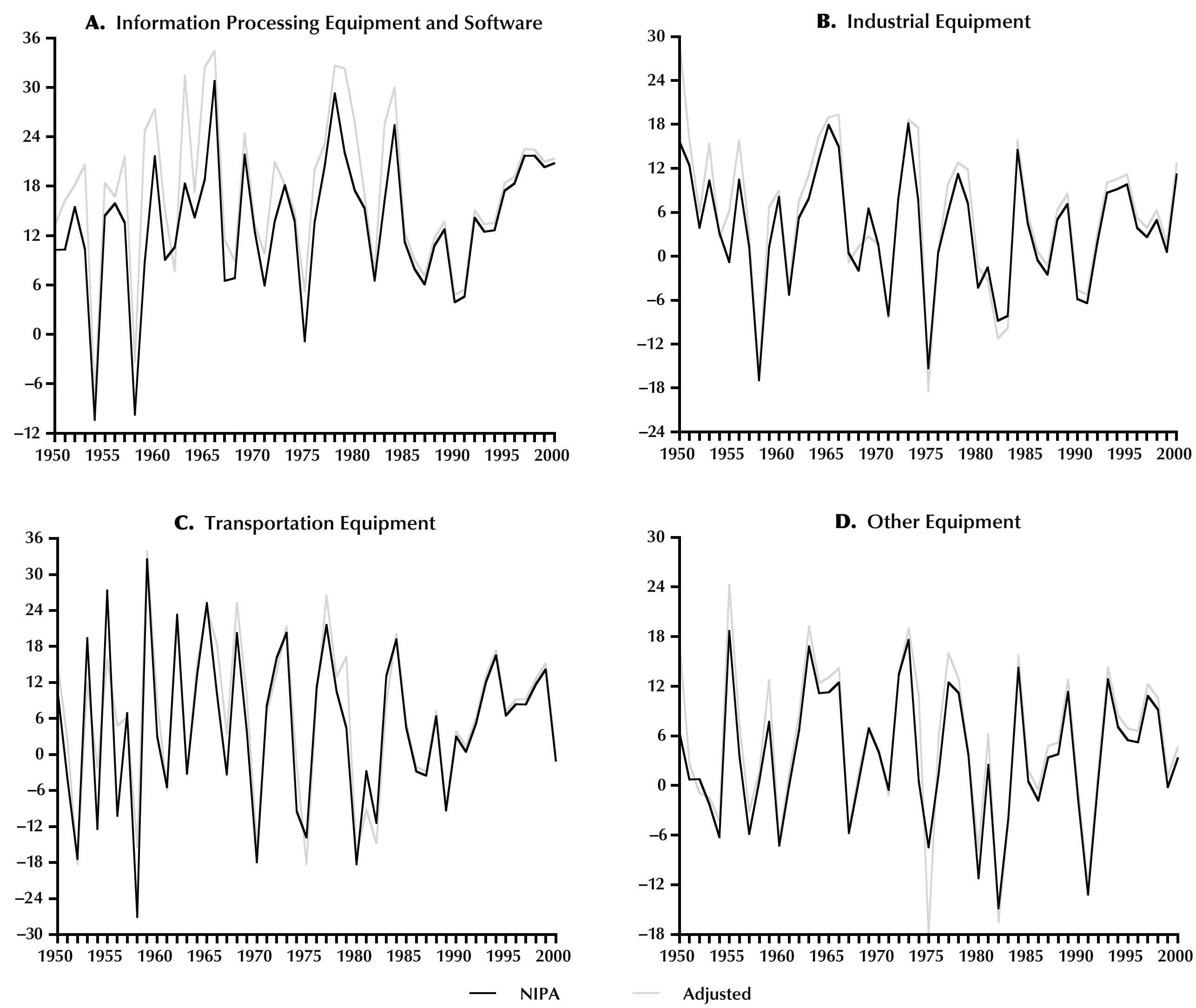
NOTE: *The official BEA statistics now incorporate quality adjustment using a hedonic-price index approach, obviating the need to use Gordon's figures.
†Software expenditures have been included in official measures only since 1999.
‡Classified by Gordon as a "secondary" category, with price data derived from primary categories.
§At the time of Gordon's study, instruments and photocopy comprised a single component.
¶Derived from data on the category of office, computing, and accounting machinery, adjusted to exclude computers and peripherals.
n.e.c.=not elsewhere classified.

SOURCE: Gordon (1990), Appendix B, Appendix C, and Tables 6.11 and 6.12.

Figure 3

Growth Rates of Major Components of Equipment and Software Investment

NIPA and Adjusted Data



of ICT growth to overall investment and output growth in the recent data.

Unfortunately, because Gordon's data set extends only through 1983, some extrapolation is necessary to use his findings to evaluate recent U.S. economic experience.

Applying Gordon's Adjustments to Contemporary Data

In order to apply Gordon's quality adjustment to contemporary NIPA data, it is necessary to make some assumptions about unmeasured quality adjustment in the post-1983 period. In addition, changes in the BEA's definitions and methodology implemented over the past two decades require some attention.

The basic procedure I adopt is to assume that the growth rate of unmeasured technological change over the 1984-2000 period is the same as Gordon's measured drift rate over the last 10 years of his sample: 1973-83. That is, Gordon's actual drift ratios are extrapolated through 2000 using the growth rates in the second column of Table 3.

Table 4

Components of Equipment and Software Investment: Growth Rates and Contributions to E&S Growth for Adjusted Data

	50s	60s	70s	80s	90s	95-00
Growth rates						
Total E&S growth	5.77	10.08	9.14	5.73	11.22	13.36
IP equipment and software	15.30	19.66	20.30	13.89	17.24	21.31
ICT	23.75	23.67	20.93	16.54	19.63	24.51
Industrial equipment	6.43	7.39	5.04	0.68	5.95	5.99
Transportation equipment	4.82	9.37	6.99	0.75	9.11	9.19
Other equipment	3.25	7.63	5.52	2.46	5.47	7.03
Contribution to E&S growth						
Percentage points (percent of E&S growth)						
Total E&S growth	5.77	10.08	9.14	5.73	11.22	13.36
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)
Contribution from:						
IP equipment and software	1.87	3.58	4.91	5.02	7.30	9.10
	(32.35)	(35.51)	(53.79)	(87.70)	(65.05)	(68.12)
ICT	1.22	2.67	3.36	4.38	6.66	8.59
	(21.09)	(26.45)	(36.81)	(76.47)	(59.38)	(64.35)
Industrial equipment	1.84	2.15	1.26	0.05	1.17	1.12
	(31.93)	(21.37)	(13.77)	(0.94)	(10.39)	(8.41)
Transportation equipment	1.24	2.52	1.76	0.12	1.85	1.92
	(21.46)	(24.99)	(19.29)	(2.17)	(16.46)	(14.34)
Other equipment	0.86	1.92	1.34	0.43	0.94	1.24
	(14.87)	(19.02)	(14.71)	(7.49)	(8.39)	(9.25)

The drift ratios are extrapolated on a component-by-component basis and then aggregated to create a quality-adjusted measure of total investment spending.[12] This disaggregated approach is preferable to a simple extrapolation of the aggregate trend for two reasons: First, several changes in the BEA's definitions and methodology have, for some components, eliminated or at least mitigated the measurement problems suggested by Gordon's study. (Specific adjustments for these changes that were made in the data extrapolation are described in the Appendix.) In addition, the procedure of reaggregating the quality-adjusted components using a chain-weighting methodology allows the role of changing expenditure shares over time to be appropriately accounted for.

Figure 3 shows annual growth rates for the four main categories of equipment and software, both for the official NIPA data and the quality-adjusted measures constructed as described above. For each category, the growth rates of the adjusted measures exceed those of the NIPA data, but decreasingly so over time. The patterns of fluctuations in the growth rates of these investment components are affected little by the adjustment—the variances of growth rates greatly exceed the magnitude of the quality adjustments.

Unmeasured Quality Change for Nonresidential Structures

In order to account for unmeasured quality change in the structures component of NFI, I utilize the estimate of Gort, Greenwood, and Rupert (1999) that the quality-improvement in nonresidential structures that is not captured in the official NIPA data amounts to approximately 1 percent growth per year. Consequently, I add 1 percentage point

[12] A similar approach to extrapolating the Gordon data set forward is described by Cummins and Violante (2002).

to each year's growth rate in real nonresidential structures over the sample period of 1947-2000, constructing an adjusted real series expressed in 1996 chain-weighted dollars. This measure is then aggregated by chain-weighting with the adjusted measure of investment in equipment and software to produce a quality-adjusted measure of total private nonresidential fixed investment.

Figure 4 shows annual growth rates for the official NIPA version of NFI and the quality-adjusted measure. As was the case for the components of equipment and software spending, the effect of the quality adjustment is to shift the growth series upward slightly, without altering the pattern of growth fluctuations evident in the original unadjusted data. On the other hand, the adjustment is clearly larger in the earlier decades of the sample period, which should tend to diminish the importance of the rise in investment spending in the late 1990s relative to earlier decades.

Finally, in order to maintain consistency in the comparison of the official NIPA with quality-adjusted data, and in their contributions to overall economic growth, an alternative quality-adjusted measure of GDP was constructed. This procedure involved unchaining NFI from GDP in the official data, then combining the resulting rest-of-GDP series with the adjusted NFI data by chain-weighting.

INVESTMENT AND GROWTH IN THE QUALITY-ADJUSTED DATA

Table 4 reports the decade-averages of quality-adjusted growth rates for the major subcomponents of equipment and software spending and their contribution to the aggregate growth rate. Comparing Table 4 with Table 2, the differences between the official and adjusted series appear to be marginal. The quality adjustment raises the average growth rates of all measures of investment, particularly in the earlier decades.

However, the acceleration of growth in information processing and software purchases and, more narrowly, in ICT spending, follows the same general pattern as in the unadjusted data: a trend of accelerating growth rates and increasing contributions to the growth rate of total nonresidential fixed investment.

Similarly, Table 5 shows that the growth rates of quality-adjusted investment and their contributions to GDP growth show the same general patterns as in the official NIPA data summarized in Table 1. The growth rates for all the quality-adjusted measures are higher than for the official NIPA data, particularly in the earlier decades of the sample period. The contributions of investment growth to GDP growth—across all levels of investment aggregation—show a trend of rising shares of GDP growth. For information processing equipment and software and for ICT spending in particular, sharp increases in the contributions to GDP growth are still evident in the 1990s.

Figures 5 and 6 show the contributions of various investment components to NFI growth and GDP growth, reproducing the time-series forecasting exercises illustrated in Figures 1 and 2. Figure 5 shows that the contributions of information processing equipment and software and ICT investment to total NFI growth both accelerated sharply during the 1990s, as was evident for the unadjusted NIPA data. In this case, however, neither measure exceeds the upper confidence bound associated with the time-series forecast: In the quality-adjusted data, it is no longer the case that the contributions of high-tech investment to total investment in the late 1990s is significantly higher than would be expected from previous trends and fluctuations in the data. Nevertheless, the contributions of these high-tech components to total investment growth exceed their forecasted paths. For 1996-2000, the contribution of ICT to the quality-adjusted growth rate of total equipment and software spending exceeds predicted values by an average of more than 1.75 percent.

Figure 4

Growth Rate of Nonresidential Fixed Investment

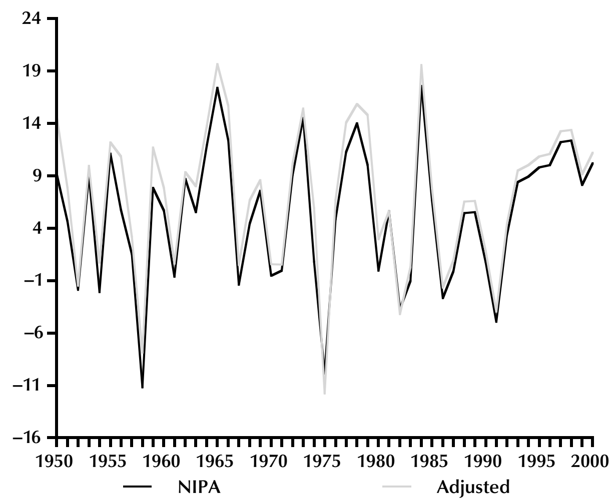


Figure 5

Contributions to Growth of Equipment and Software Investment

Adjusted Data and Forecasts

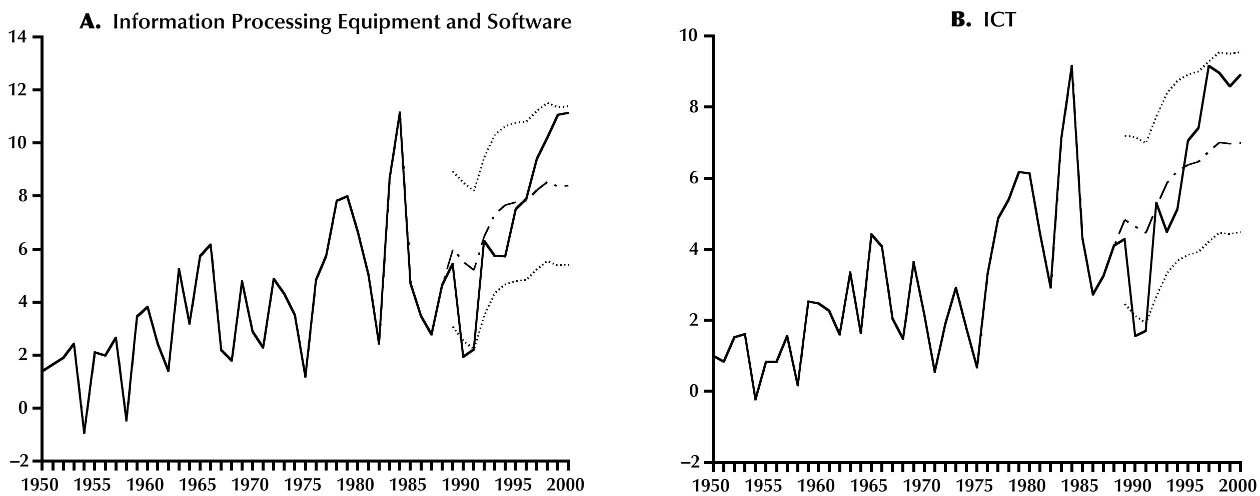


Table 5

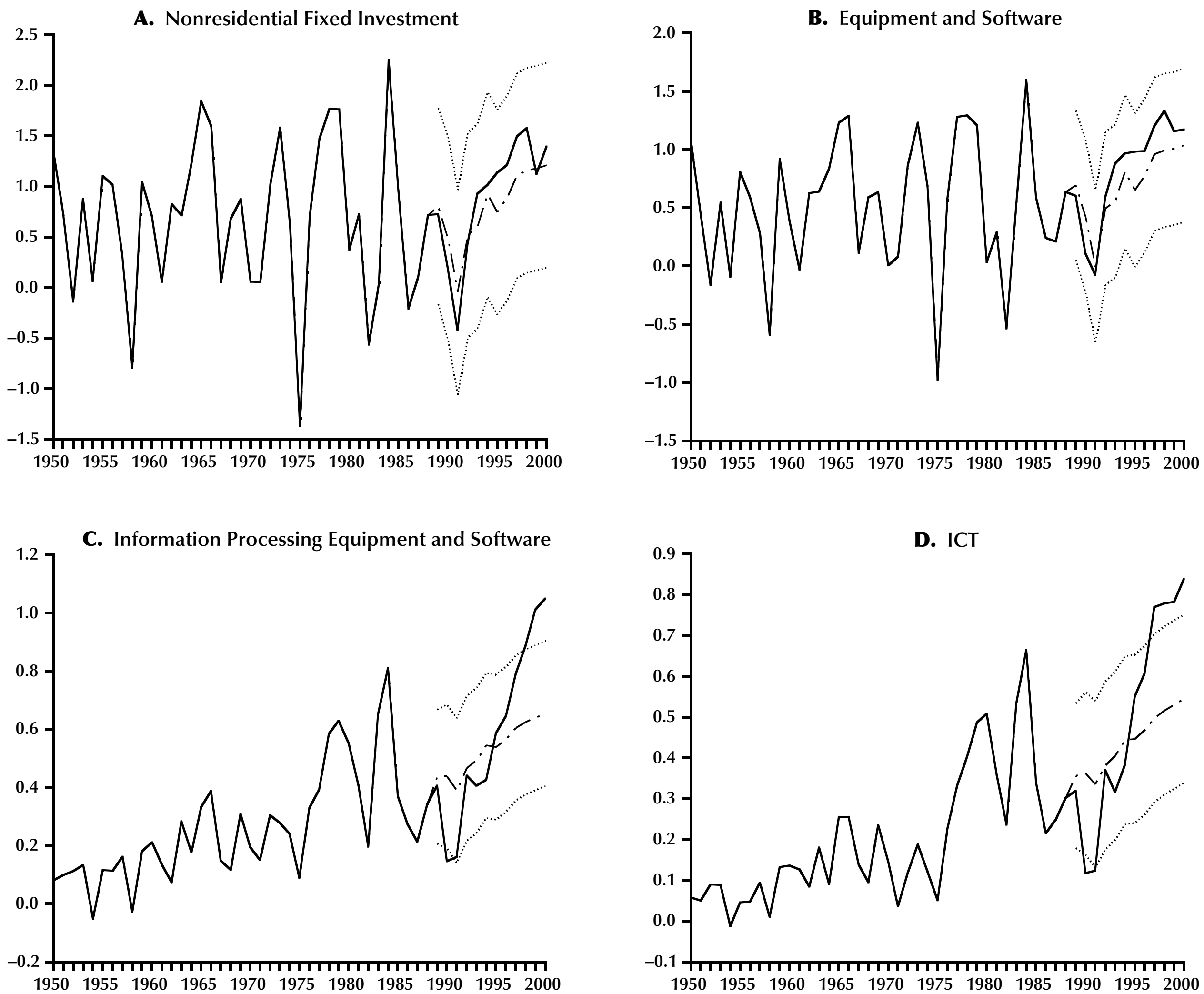
Output and Investment: Growth Rates and Contributions of Investment to GDP Growth for Adjusted Data

	50s	60s	70s	80s	90s	95-00
Growth rates						
GDP	3.76	4.37	3.44	3.32	3.40	4.31
Nonresidential fixed investment	5.49	8.33	7.45	4.31	8.87	11.60
Structures	5.19	5.52	4.49	1.85	2.66	6.49
Equipment and software	5.78	10.08	9.15	5.73	11.23	13.37
IP equipment and software	15.30	19.66	20.31	13.89	18.33	23.48
ICT	23.75	23.67	20.93	16.54	19.63	24.51
Contribution to GDP growth						
Percentage points (percent of GPD growth)						
GDP	3.76	4.37	3.44	3.32	3.40	4.31
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)
Contribution from:						
Nonresidential fixed investment	0.50	0.79	0.80	0.49	1.04	1.45
	(13.18)	(18.15)	(23.25)	(14.90)	(30.45)	(33.63)
Structures	0.18	0.20	0.17	0.07	0.08	0.21
	(4.85)	(4.61)	(4.87)	(2.13)	(2.23)	(4.91)
Equipment and software	0.31	0.59	0.63	0.42	0.96	1.24
	(8.33)	(13.54)	(18.38)	(12.77)	(28.22)	(28.71)
IP equipment and software	0.10	0.21	0.34	0.37	0.64	0.88
	(2.69)	(4.81)	(9.88)	(11.19)	(18.86)	(20.33)
ICT	0.07	0.16	0.23	0.32	0.59	0.83
	(1.75)	(3.58)	(6.75)	(9.75)	(17.32)	(19.31)

Figure 6

Contributions to Growth of GDP

Adjusted Data and Forecasts



Note also that the magnitudes of the declines in these growth contributions during the 1990-91 recession fall below their forecasted values, as was the case with the unadjusted NIPA data.

Figure 6 shows the contributions of investment spending to GDP growth using the quality-adjusted data. For the broader measures of investment—total private nonresidential investment and total equipment and software investment—the patterns are nearly identical to the unadjusted data: Actual growth contributions fall below their forecasted paths early in the 1990s and exceed the paths later in the decade, but remain well within the confidence bounds.

For the more narrow measures of high-tech investment, the quality adjustment makes somewhat more noticeable difference in the patterns of contributions to GDP growth. Nevertheless, the comparisons of actual to forecasted growth contributions show the same overall relationships as found for the unadjusted data. In the late 1990s, the contribution of high-tech investment spending to overall economic growth was significantly higher than previous data would have suggested. Only the magnitude by which the growth contributions fall outside the forecast confidence intervals is altered by the quality adjustment.

CONCLUSION

This article has focused on the issue of quality adjustment in the measurement of investment in the national income and product accounts. The rapidly evolving nature of information processing and communications technologies has necessitated careful accounting of quality improvement in high-tech investment sectors. Because it is precisely these sectors which account for the investment boom of the late 1990s, a question arises as to whether it is the measurement of quality improvement itself which accounts for the remarkable growth of the past several years.

This paper addresses that issue by adjusting the investment data for other sources of quality improvement that may have gone unmeasured in the official BEA measures. Although the growth that can be attributed to such unmeasured quality improvement is arguably quite large in some sectors, the variances of investment growth rates are so high that they overwhelm the impact of the quality adjustment. As a result, tests for evaluating how important high-tech investment is in explaining the rapid growth rates of the late 1990s are largely invariant to this accounting for quality. Whether or not one accounts for unmeasured quality change in other capital goods sectors, the contribution of high-tech investment GDP growth in the late 1990s is significantly higher than would have been expected from past patterns of growth and cyclical fluctuations.

Moreover, the contribution of high-tech investment spending to the variability of total investment growth is also reflected in greater-than-forecasted declines in investment during the recession of the early 1990s. Evidently, as ICT technologies have become a more important component of investment spending, they have had the effect of increasing the volatility of investment. In that context, the sharp decline in investment spending seen in 2001 suggests a continuation of this highly variable growth pattern.

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Appendix

EXTRAPOLATING AND UPDATING THE GORDON DATA

Of the recent changes to the BEA's definitions and methodology, most apply to the elements of information processing equipment and software. First, the category previously known as office, computing, and accounting machinery (OCAM) was divided into two categories: computers and peripheral equipment and office and accounting equipment. Most of the unmeasured quality change for this component was in the computers and peripherals category, for which a hedonic price index approach was adopted in late 1985. Because current BEA practice carefully accounts for quality change, Gordon's calculations are superfluous for evaluating the growth rate of computer equipment. For the remaining elements of that category, data from Gordon's Tables 6.1 and 6.2 (which detail the construction of a deflator for OCAM) were used to separate out the computer component, with the remaining drift ratio to be applied to the office and accounting machinery component.

Software was incorporated as a component of fixed investment only in 1999, and was therefore not examined by Gordon. The BEA applies a hedonic approach to some components of software investment: In particular, a hedonic index is used to deflate prepackaged software, while in-house software is deflated using an input cost index. Custom software is deflated using a weighted-average of these two deflators. This practice amounts to applying a hedonic price index to about one-half of all software.[13] For the purpose of this study, I assume that the BEA methodology accurately measures quality change in this component.

Next to computers, the largest drift ratios measured by Gordon were for communications equipment. In particular, Gordon found that the official price index for telephone transmission and switching equipment (by far the largest item in the communications equipment category) vastly understated improvements associated with electronics and transmissions technologies in the 1960s and 1970s. In 1997, the BEA introduced a quality-adjusted price index for telephone switching and switchboard equipment and carried back these revisions to 1985 in the 1999 comprehensive revision of the national accounts.[14] Because these revisions addressed the most serious concerns that Gordon raised about the measurement of quality change in communications equipment, I assume that the post-1985 data accurately reflect quality improvements. Consequently, I use his drift ratios and extrapolations only for years prior to 1985.

Another category that requires special attention is automobiles. As shown in Table 3, the automobile component showed a negative drift ratio over the 1973-83 period—suggesting that the BEA overestimated quality change over the decade. However, Gordon explains this finding as the result of a "spurious decline in the NIPA automobile deflator during 1980-83"[15] that he attributed to the use of a deflator for used cars that is inconsistent with quality change measured in the index for new cars. (Used cars sold from business enterprises to households—reflecting a reclassification from business capital to consumer durables—represent a factor that subtracts from investment.) In the absence of this inconsistency, Gordon notes that the drift ratio for automobiles would be close to zero for the 1973-83 period. In 1987, the BEA began to adjust used automobile prices by applying a quality-adjustment factor derived from its treatment of new car prices.[16] In the comprehensive revision of 1991, this change was carried back to years prior to 1984.[17] This change altered both the nominal and real data series on investment spending for automobiles and largely eliminated the "spurious decline" in the automobile deflator for 1980-83. Consequently, in extrapolating Gordon's data on quality change for autos, I assume a drift ratio equal to zero for the post-1983 period.[18]

Some other reclassifications of the components of equipment investment proved to be simple to address: For example, the reclassification in 1997 of analytical instruments from the "photocopy and related equipment" category to the "instruments"

[13] See Parker (2000) and Landefeld and Fraumeni (2001).

[14] Moulton and Seskin (1999).

[15] Gordon (1990, p. 538).

[16] Fox (1987).

[17] Fox and Parker (1991).

[18] In addition, because the BEA's methodological changes affected both nominal and real series, I use Gordon's actual price index figures (rather than applying his drift ratios directly to the contemporary deflator series) for years prior to 1983.

category required no special adjustments, because Gordon's drift ratio applies to the combined "instruments and photocopy equipment" category that was in use at the time.[19] Similarly, a reclassification of some equipment from "metalworking machinery" to "special industry machinery" was also innocuous, since Gordon found that the deflator for the latter was based on a subset of raw prices from the former. In calculating his drift ratios, Gordon simply applied the same factor to both categories.[20]

Finally, there is the issue of aggregation technique. At the time of his writing, Gordon criticized the BEA's continuing practice of using fixed-weight deflators. Particularly in light of his modifications accounting for quality change, a fixed-weight approach tends to underestimate the importance of goods that are declining in price (or increasing in quality) while overstating the importance of goods that have rising prices. Gordon proposed the use of a Törnqvist index, which uses share weights from adjacent periods to construct deflators for both the individual components of equipment purchases and for aggregating the totals. The BEA subsequently adopted a "Fisher ideal" chain-weighting formula that is similar to the Törnqvist approach in that it incorporates share weights from adjacent periods that are allowed to evolve over time. While the two approaches are very similar, they are not identical. For the purposes of this study, however, I assume that the two methodologies are essentially interchangable. While I use Gordon's Törnqvist-aggregated measures for disaggregating and reaggregating the elements of OCAM into their contemporary definitional categories, I use the BEA's chain-weighting formula for aggregating the quality-adjusted components of investment spending into measures that are directly comparable to the NIPA data.

[19] This reclassification was associated with the incorporation of new data from the 1992 Input-Output accounts. See Taub and Parker (1997).

[20] The "special industry machinery" component was one of six that Gordon referred to as "secondary" categories, for which the underlying price data overlapped with the other 16 "primary" categories.

Why Are Stock Market Returns Correlated with Future Economic Activities?

Hui Guo

Stock price has been found to provide important information about future economic activities. Fama (1981), Fischer and Merton (1984), and Barro (1990), among many others, document a positive relation between stock market return and subsequent growth in investment and output. These findings are consistent with rational expectations asset pricing models, in which stock price is equal to the sum of discounted future cash flows or dividends. An *unexpected* increase in the stock price indicates that (i) future dividend growth is higher and/or (ii) future discount rates are lower than previously anticipated. Given that the dividend is an important component of gross domestic product (GDP) and is also likely to be positively correlated with the other components of GDP, the stock price increase may merely reflect higher expected future output. On the other hand, lower discount rates are associated with higher investment and, therefore, higher output.[1] Moreover, recognizing a time-varying risk premium, Lettau and Ludvigson (2001b) show that the q theory of investment implies an important relation between the expected stock market return and investment. That is, lower expected stock market return implies lower future stock price and higher future capital cost; accordingly, investment falls over long horizons.

The analysis above shows that stock returns are correlated with future economic activities through different channels. In this paper, I address the relative importance of these mechanisms by using Campbell and Shiller's (1988) method to decompose excess stock market return, $e_{M,t}$, into three parts: expected return, $E_{t-1}e_{M,t}$; a shock to the expected future return,

$$-(E_t - E_{t-1})\sum_{j=1}^{\infty} \rho^j e_{M,t+j}\,;$$

and a shock to the expected future dividend growth,[2]

$$(E_t - E_{t-1})\sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+j}\,.$$

I find that a positive shock to the expected future dividend growth is associated with higher future GDP growth. Contrary to the conventional wisdom, however, dividend shocks are rather weak predictors for economic activities. For example, their forecasting power concentrates on the next four quarters, of which dividend shocks explain only about 2 percent of variations in GDP growth. I find similar results for the GDP components as well. In contrast, the expected return, especially, and shocks to the expected future return exhibit strong predictive ability for economic activities. However, their predictive patterns are quite different: while shocks to the expected future return are positively (negatively) correlated with future investment over short (long) horizons, the expected return is negatively (positively) correlated with future investment over short (long) horizons. As a result, the forecasting power of excess stock market return is considerably compromised. For example, it explains essentially no variations in one-quarter-ahead investment growth, while the three components jointly account for 4 percent. Also, excess stock market return explains only 2 percent of variations in the next three years' investment growth, compared with 13 percent by the three components.

Intuitively, a positive innovation in the dividend indicates greater future economic growth. However, the forecasting power of dividend shocks is moderate because my decompositions show that they account for only a small portion of variations in excess stock market return. The relation between the expected return, $E_{t-1}e_{M,t}$, and future investment

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William Bock provided research assistance.

[1] According to the q theory of investment, a negative shock to discount rates should increase stock price and investment simultaneously. However, Lamont (2000) argues that there are intertemporal shifts in these relationships because of lags between investment decisions and investment expenditures. His results help explain why, according to the data, stock return is negatively correlated with contemporaneous investment and positively correlated with subsequent investment.

[2] Actually, there is an extra term: the shock to the real risk-free rate,

$$-(E_t - E_{t-1})\sum_{j=0}^{\infty} \rho^j r_{f,t+j}\,.$$

However, Campbell and Ammer (1993) find that it accounts for very few variations in excess stock market return. For simplicity, I assume that its value is zero in this paper.

is consistent with Lettau and Ludvigson (2001b), who show that the two variables are negatively correlated in the short run and are positively correlated in the long run. Similarly, because the shock to the expected future return at period t,

$$-(E_t - E_{t-1})\sum_{j=1}^{\infty} \rho^j e_{M,t+j},$$

is negatively correlated with the expected return at period $t+1$, $E_t e_{M,t+1}$, it should also be negatively correlated with investment in the long run, even though the two are positively correlated in the short run. In other words, an appreciation in stock price may imply either an increase or decrease in future investment, depending on whether such an appreciation in price is due to (i) a negative shock to the expected future return or (ii) to the fact that the stock price is expected to be high.[3] My results, therefore, explain why the predictive power of stock market returns is rather limited, as argued by many authors (e.g., Stock and Watson, 1999).

Later in the article, I discuss the stock market return predictability and then decompose excess stock market returns. I show forecasting ability of these components for future economic activities and then offer conclusions.

STOCK MARKET RETURN PREDICTABILITY

In the past two decades, financial economists have documented mounting evidence against the random walk hypothesis of stock price. For example, Campbell, Lo, and MacKinlay (1997) provide evidence that dividend yield and the stochastically detrended risk-free rate contain information about future stock price movements.[4,5] Lettau and Ludvigson (2001a) find that fluctuations in the consumption-wealth ratio are strong predictors of future stock market returns. Moreover, Guo (2002) shows that past stock market variance has significant predictive ability as well; and, interestingly, such predictive ability is greatly enhanced if the consumption-wealth ratio is also included in the forecasting equation.

Table 1 replicates some results of the predictability of stock market return documented in the early literature. The informational variables include lagged excess stock market return, $e_{M,t}$; the dividend yield, dp_t; the stochastically detrended risk-free rate, $rrel_t$; the consumption-wealth ratio, cay_t; and past stock market variance, $\sigma^2_{M,t}$. I use quarterly data from 1953:Q1 to 2000:Q4, and Appendix A provides details about that data. The first five rows present the univariate regression results. I find that, while $rrel_t$, cay_t, and $\sigma^2_{M,t}$ forecast one-quarter-ahead excess stock market return, $e_{M,t}$ and dp_t enter the forecasting equation insignificantly. Row 6 is the regression result of excess stock market return on all the informational variables except $\sigma^2_{M,t}$. Again, $rrel_t$ and cay_t are both statistically significant and the adjusted R^2 is about 12 percent. I add $\sigma^2_{M,t}$ as an additional regressor to the multivariate regression in row 7. Consistent with Guo (2002), $rrel_t$, cay_t, and $\sigma^2_{M,t}$ are highly significant and the adjusted R^2 jumps to 20 percent! The substantial improvement in the forecasting ability is explained by the fact that, while $\sigma^2_{M,t}$ and cay_t are negatively correlated, they both enter the excess stock market return equation with a positive sign. To summarize, evidence suggests that a large portion of variations in excess stock market return is predictable.

I want to emphasize that stock price predictability does not necessarily contradict the stock market efficiency hypothesis. This point is clearly demonstrated in Merton's (1973) intertemporal capital asset pricing model (ICAPM), which can be summarized by equation (1a):

$$\text{(1a)} \qquad E_t e_{M,t+1} = \gamma E_t \sigma^2_{M,t+1} + \lambda E_t \sigma_{MF,t+1}.$$

The conditional excess stock market return, $E_t e_{M,t+1}$ (defined as the difference between the conditional stock market return, $E_t r_{M,t+1}$, and the risk-free rate, $r_{f,t+1}$), is a linear function of its conditional variance, $E_t \sigma^2_{M,t+1}$, and its covariance with investment opportunities, $E_t \sigma^2_{MF,t+1}$. The coefficient γ is a measure of relative risk aversion, and the coefficient λ is a function of the model's underlying parameters. I call the first term of equation (1a) the risk component and the second term the hedge component. It is well known that stock market variance is serially correlated in the data; also, there is no particular reason to believe that the covariance between excess

[3] A simple model developed by Guo (2001) makes this point clear. If the conditional stock market return is proportional to the risk, the author shows that excess stock market return is positively correlated with lagged stock market variance and is negatively correlated with current variance. Given that stock market variance is negatively correlated with future output, the positive relation between excess return and lagged variance weakens the forecasting power of the former. His model, therefore, explains why stock market variance drives out return in forecasting GDP growth, as documented by Campbell et al. (2001).

[4] The stochastically detrended risk-free rate is the risk-free rate less its average over the last four quarters.

[5] Lettau and Ludvigson (2001a) find that the dividend yield loses its forecasting ability when the sample period is extended to the later 1990s, a result I reproduce later in the paper.

Table 1

Forecasting Quarterly Excess Stock Market Return

Row	$e_{M,t}$	dp_t	$rrel_t$	cay_t	$\sigma^2_{M,t}$	$\bar{R}^2$
1	0.065					–0.00
	(1.054)					
2		0.009				0.01
		(1.459)				
3			–0.020			0.07
			(–3.929)			
4				1.931		0.08
				(3.211)		
5					4.601	0.03
					(2.825)	
6	–0.083	0.002	–0.018	1.784		0.12
	(–1.658)	(0.254)	(–4.783)	(3.861)		
7	0.029	0.002	–0.014	2.333	7.391	0.20
	(0.569)	(0.537)	(–4.030)	(5.579)	(5.249)	

NOTE: This table reports the ordinary least-squares (OLS) regression results of excess stock market return, $e_{M,t+1}$, on informational variables, including the lagged excess stock market return, $e_{M,t}$; the dividend yield, dp_t; the stochastically detrended risk-free rate, $rrel_t$; the consumption-wealth ratio, cay_t; and the realized stock market variance, $\sigma^2_{M,t}$. Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The data are quarterly and span from 1953:Q1 to 2000:Q4. See Appendix A for a description of the data.

stock market returns and investment opportunities is constant or that its coefficient is zero. In general, the expected stock market return is not constant and stock market returns are predictable.

While the early literature has emphasized the risk component, Guo (2000) shows that the hedge component is also important in understanding the time-varying equity premium in a limited stock market participation model. As shown in equation (1b), the equity premium also has two components in the model developed by Guo (2000)[6]:

(1b)

$$E_t e_{M,t+1} + E_t \frac{\sigma^2_{M,t+1}}{2} \approx \gamma E_t \sigma_{MC,t+1} + r^f_{1,t+1} - \min\{r^f_{1,t+1}, r^f_{2,t+1}\},$$

where $E_t \sigma_{MC,t+1}$ is the covariance between the shareholder's consumption growth and stock market returns and $r^f_{1,t+1}$ and $r^f_{2,t+1}$ are the shareholder's and the non-shareholder's shadow risk-free rates, respectively. While the first term, $\gamma E_t \sigma_{MC,t+1}$, is proportional to the risk component in equation (1a), the second term, $r^f_{1,t+1} - \min\{r^f_{1,t+1}, r^f_{2,t+1}\}$, can be thought of as a liquidity premium because it reflects the fact that the shareholder cannot use stocks to hedge the income risks because of the constraints of limited stock market participation. Moreover, such a liquidity premium is small (large) when the stock price is high (low); therefore, it is positively correlated with the dividend yield. Interestingly, Guo (2000) also predicts that, when the dividend yield is low, stock market variance should be negatively correlated with the dividend yield. Thus, given that the consumption-wealth ratio is equivalent to the dividend yield in Guo (2000), his model well explains the empirical evidence documented in Table 1.[7]

[6] The variance term

$$E_t \frac{\sigma^2_{M,t+1}}{2}$$

on the left-hand side of equation (1b) is the adjustment for Jensen's inequality.

[7] Campbell, Lo, and MacKinlay (1997) explain that the dividend yield forecasts stock market returns because it can be written as a function of expected future excess stock market return and dividend growth. Similarly, Lettau and Ludvigson (2001a) show that the consumption-wealth ratio is also a function of expected future excess stock market return and consumption growth. The two variables, therefore, are equivalent in an exchange economy (e.g., Guo, 2000). Despite their close theoretical link, the consumption-wealth ratio demonstrates much stronger predictive power than the dividend yield does, possibly because the former is a better measure of its theoretical counterpart than the latter is.

A DECOMPOSITION OF EXCESS STOCK MARKET RETURN

Given strong evidence of stock return predictability, in this section, I adopt Campbell and Shiller's (1988) log-linearization method to decompose excess stock market return into three parts: expected return, a shock to the expected future return, and a shock to the expected future dividend growth. The advantages of this approach are tractability and accuracy.

The continuously compounded stock market return, $r_{M,t}$, is defined as

(2) $$r_{M,t} = \log(P_{M,t} + D_{M,t}) - \log(P_{M,t-1}),$$

where $P_{M,t}$ is the stock price at the end of period t and $D_{M,t}$ is the dividend paid out during period t. Throughout this paper, I use upper case to denote the level and lower case to denote the log. Using a first-order Taylor expansion around the steady state of the log dividend price ratio $\overline{d-p}$, equation (2) can be rewritten as a first-order difference equation for the stock price:

(3) $$r_{M,t} \approx k + \rho p_{M,t} - p_{M,t-1} + (1-\rho) d_{M,t},$$

where

$$\rho = \frac{1}{1+\exp(\overline{d-p})},$$

$$k = -\log(\rho) - (1-\rho)\log(\frac{1}{\rho} - 1).$$

Campbell, Lo, and MacKinlay (1997) report that the annual dividend yield is about 4 percent in the historical data. Accordingly, I set ρ to 0.99 for the quarterly data in this paper.

Solving equation (3) forward and imposing the transversality condition

$$\lim_{j \to \infty} \rho^j P_{M,t+j} = 0,$$

the stock price can be written as a function of future dividend flows and discount rates:

(4) $$p_{M,t-1} = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^j [(1-\rho) d_{M,t+j} - r_{M,t+j}].$$

Equation (4) is simply an accounting identity, which also holds ex ante:

(5) $$p_{M,t-1} = \frac{k}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j [(1-\rho) d_{M,t+j} - r_{M,t+j}].$$

Substituting equation (5) into equation (3), I then decompose the realized excess stock market return into three parts: expected return, a shock to the expected future dividend growth, and a shock to the expected future return.

(6) $$r_{M,t} - E_{t-1} r_{M,t} = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+j} - (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{M,t+j}.$$

For the excess stock market return, $e_{M,t+1} = r_{M,t+1} - r_{f,t+1}$, where $r_{f,t+1}$ is the real risk-free rate, I can rewrite equation (6) as

(7) $$e_{M,t} - E_{t-1} e_{M,t} = (E_t - E_{t-1})(\sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+j} - \sum_{j=0}^{\infty} \rho^j r_{f,t+j} - \sum_{j=1}^{\infty} \rho^j e_{M,t+j}).$$

I assume that, $x_{1,t}, x_{2,t}, \ldots x_{n,t}$ are n state variables that predict excess stock market return, and the vector $X_t = [e_{M,t}, x_{1,t}, x_{2,t}, \ldots x_{n,t}]$ follows a first order vector autoregression (VAR) process

(8) $$X_t = A + BX_{t-1} + \varepsilon_t,$$

where A is an $(n+1)$ by 1 vector of constants, B is an $(n+1)$ by $(n+1)$ coefficient matrix, and ε_t is an $(n+1)$ by 1 vector of white noise. Then, the expected excess stock market return, $E_{t-1} e_{m,t}$, is equal to $e1' B_1 X_1$, where $e1$ is an n by 1 vector $[1,0,\ldots,0]$. As shown in Appendix B, the shock to the expected future return,

$$-(E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j e_{M,t+j},$$

is equal to $e1' \rho B (I - \rho B)^{-1} \varepsilon_t$, where I is an $(n+1)$ by $(n+1)$ identity matrix. Campbell and Ammer (1993) find that the shock to the expected future real risk-free rate,

$$-(E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j r_{f,t+j},$$

accounts for very few variations in excess stock market return. For simplicity, I assume that its value is zero; and therefore, the shock to the expected future dividend growth,

$$(E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+j},$$

is approximately equal to $e_{M,t} - E_{t-1} e_{M,t} - e1' \rho B (I - \rho B)^{-1} \varepsilon_t$. Furthermore, I denote the shock to the expected future return,

$$-(E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j e_{M,t+j},$$

Table 2

Vector Autoregression of Excess Stock Market Return

	$e_{M,t}$	dp_t	$rrel_t$	cay_t	$\sigma^2_{M,t}$	$\bar{R}^2$
$e_{M,t+1}$	0.029	0.002	–0.014	2.333	7.391	0.20
	(0.569)	(0.537)	(–4.030)	(5.579)	(5.249)	
dp_{t+1}	–0.461	0.980	0.061	–5.544	–24.104	0.95
	(–2.183)	(76.929)	(5.130)	(–4.191)	(–5.894)	
$rrel_{t+1}$	0.753	–0.083	0.706	–8.381	–25.995	0.51
	(0.975)	(–1.216)	(14.113)	(–1.529)	(–1.421)	
cay_{t+1}	–0.050	0.001	–0.001	0.926	0.184	0.80
	(–6.911)	(1.559)	(–1.684)	(25.903)	(1.668)	
$\sigma^2_{M,t+1}$	0.004	–0.000	0.000	–0.078	0.388	0.24
	(1.400)	(–0.880)	(0.929)	(–2.930)	(5.274)	

NOTE: This table reports the ordinary least-squares (OLS) regression results of the VAR system specified by equation (8). Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The data are quarterly and span from 1953:Q1 to 2000:Q4. See Appendix A for a description of the data.

Table 3

Summary Statistics

	$e_{M,t}$	$E_{t-1}e_{M,t}$	$\eta_{e,t}$	$\eta_{d,t}$
Panel A: Mean and standard error				
Mean	0.074	0.074	0.000	0.000
Standard error	0.324	0.151	0.278	0.147
Panel B: Covariance and correlation				
$e_{M,t}$	**0.105**	0.47	0.76	0.27
$E_{t-1}e_{M,t}$	**0.023**	**0.023**	0.00	0.00
$\eta_{e,t}$	**0.069**	**0.000**	**0.077**	–0.21
$\eta_{d,t}$	**0.013**	**0.000**	**–0.009**	**0.022**

NOTE: This table reports the mean, standard error, covariance (lower triangle of Panel B, in bold), and correlation (upper triangle of Panel B) of the excess stock market return in its three components. The decomposition is based on the VAR estimation reported in Table 2.

by $\eta_{e,t}$ and the shock to the expected future dividend growth,

$$(E_t - E_{t-1})\sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+j},$$

by $\eta_{d,t}$. Note, $\eta_{e,t}$ and $\eta_{d,t}$ are orthogonal to $E_{t-1}e_{M,t}$ by definition.

Table 2 reports the ordinary least-squares (OLS) estimate of the VAR system specified in equation (8). The state variables include all the forecasting variables used in Table 1. I adopt a VAR (1) specification because it is consistent with the Schwarz Bayesian information criterion and the Akaike information criterion. One interesting observation is that the coefficient on its own lag is pretty large for dp_t, $rrel_t$, and cay_t, whereas it is only 0.38 for $\sigma^2_{M,t}$. Therefore, unlike other forecasting variables, $\sigma^2_{M,t}$ captures relatively high-frequency variations in excess stock market return.

Summary statistics for excess stock market return, $e_{M,t}$, and its three components are reported in Table 3. By construction, shocks to the expected future return, $\eta_{e,t}$, and shocks to the expected future dividend growth, $\eta_{d,t}$, both have zero means. How-

Figure 1

Realized Excess Stock Market Return

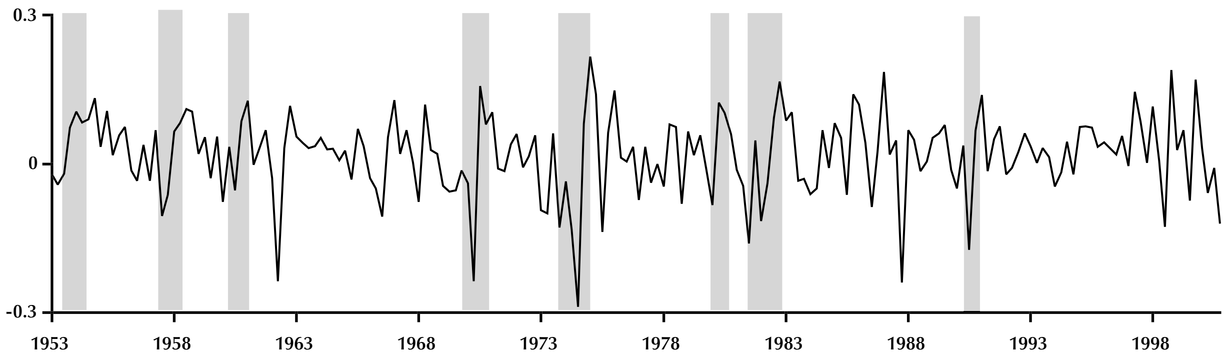
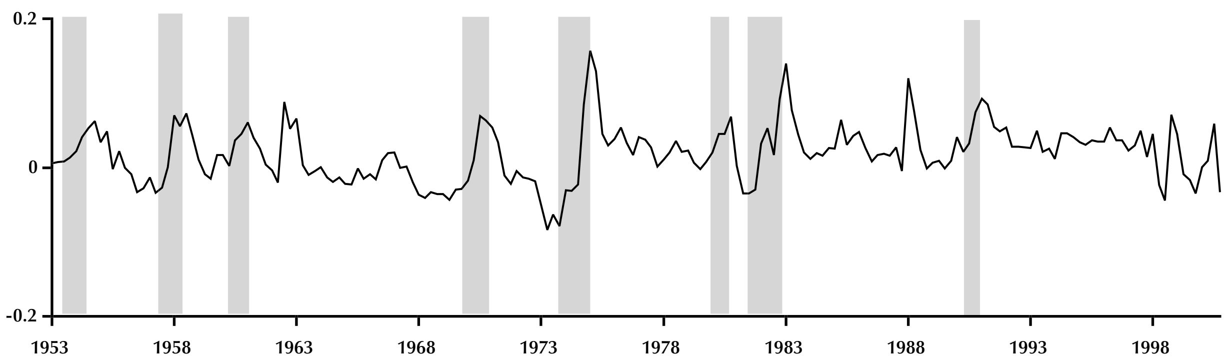


Figure 2

Expected Excess Stock Market Return



ever, the standard error of $\eta_{e,t}$ is almost twice as large as that of $\eta_{d,t}$. The expected return, $E_{t-1}e_{M,t}$, has the same mean as, but a much smaller standard error than, that of $e_{M,t}$. Moreover, the covariance between $\eta_{e,t}$ and $e_{M,t}$ is about 66 percent of the variance of $e_{M,t}$, while it is 22 percent for $E_{t-1}e_{M,t}$ and 12 percent for $\eta_{d,t}$. Similarly, $\eta_{e,t}$ has the largest correlation coefficient with $e_{M,t}$, followed by $E_{t-1}e_{M,t}$ and $\eta_{d,t}$. Therefore, $\eta_{e,t}$ and $E_{t-1}e_{M,t}$ account for the vast majority of variations in $e_{M,t}$, while $\eta_{d,t}$ is relatively unimportant in explaining stock price movements. In other words, stock price is not sensitive to the dividend news. My results are consistent with those reported in the early literature (e.g., Campbell and Shiller, 1988), although the two papers adopt different forecasting variables.

Figures 1 through 4 plot excess stock market return and its three components, with the shaded areas indicating recessions, the dates of which were determined by the National Bureau of Economic Research. Figure 1 shows that stock price seems to decrease (increase) at the beginning (end) of recessions. However, it fluctuates dramatically over time and displays little business cycle pattern. This assessment is consistent with the conventional skepticism about stock price as a leading indicator. The picture is quite different for the expected return. Figure 2 shows that the expected return always increases during recessions and decreases during expansions. In only two occasions, namely, the second quarter of 1962 and the fourth quarter of 1987, were the sharp increases in the expected return not associated with recessions. In the first case, the economy slowed down significantly in the following quarters. In the second case, the expected return was driven up solely by the dramatic increase in stock market

Figure 3

Shock to the Expected Future Return

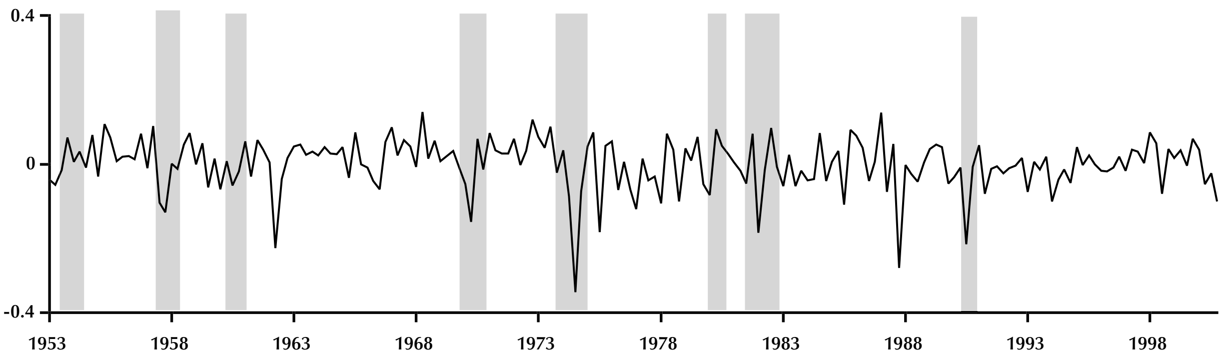
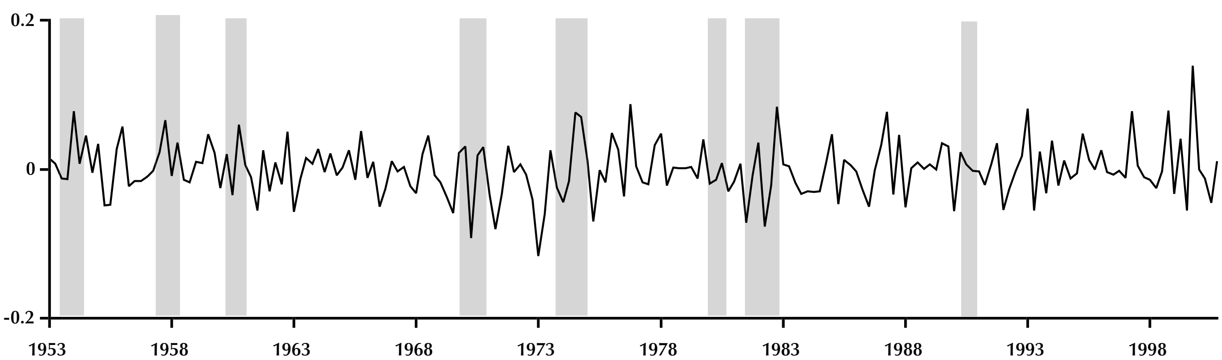


Figure 4

Shock to the Expected Future Dividend Growth



variance because of the October 19, 1987, stock market crash, which was unusual and short-lived. My findings of a strongly cyclical expected return should not be a surprise because forecasting variables such as the consumption-wealth ratio, the stochastically detrended risk-free rate, and past stock market variance all display strong business cycle patterns. In contrast, Figures 3 and 4 show that shocks to the expected future return and shocks to the expected future dividend growth do not move in tandem very much with business cycles.

STOCK MARKET RETURNS AND FUTURE ECONOMIC ACTIVITIES

Excess stock market return, $e_{M,t}$, is high because (i) it is expected to be high or $E_{t-1}e_{M,t}$ is high, (ii) there is a negative shock to the expected future return or $\eta_{e,t}$ is high, or (iii) there is a positive shock to the expected future dividend growth or $\eta_{d,t}$ is high. In this section, I analyze the relative importance of these components in forecasting economic activities.

Fixed Private Nonresidential Investment

Table 4 reports the long-horizon regression results of the fixed private nonresidential investment growth on excess stock market return and its three components.[8] For horizon H, the dependent variable is the investment growth rate from time $t+1$ to $t+1+H$. Row 1 shows that excess stock market return, $e_{M,t}$, is always positively correlated with future investment growth. Its predictive power as measured by the adjusted R^2 first increases then decreases and peaks at four quarters, at which it

8 I obtain qualitatively similar results if I also include the lagged dependent variable as a regressor.

Table 4

Forecasting Fixed Nonresidential Investment Growth

Row	Regressor	Forecast horizon 1	2	4	8	12	16
1	$e_{M,t}$	0.01	0.11	0.26	0.33	0.24	0.13
		(0.40)	(2.82)	(3.41)	(3.25)	(2.60)	(1.21)
		[0.00]	[0.04]	[0.08]	[0.06]	[0.02]	[0.00]
2	$E_{t-1}e_{M,t}$	–0.09	–0.01	0.38	1.05	1.20	1.09
		(–2.20)	(–0.14)	(1.77)	(3.72)	(4.21)	(3.08)
		[0.02]	[–0.00]	[0.04]	[0.14]	[0.14]	[0.09]
3	$\eta_{e,t}$	0.06	0.15	0.20	0.03	–0.12	–0.21
		(1.62)	(2.59)	(2.26)	(0.35)	(–1.11)	(–1.67)
		[0.02]	[0.07]	[0.03]	[–0.01]	[–0.00]	[0.01]
4	$\eta_{d,t}$	–0.08	–0.05	0.10	0.33	0.31	0.23
		(–1.18)	(–0.42)	(0.76)	(2.12)	(1.67)	(1.08)
		[0.01]	[–0.00]	[–0.00]	[0.01]	[0.00]	[–0.00]
5	$\eta_{e,t}+\eta_{d,t}$	0.04	0.14	0.22	0.12	–0.04	–0.15
		(1.42)	(2.92)	(2.75)	(1.23)	(–0.48)	(–1.34)
		[0.01]	[0.05]	[0.05]	[0.00]	[–0.01]	[0.00]
6	$E_{t-1}e_{M,t}$	–0.09	–0.01	0.38	1.04	1.19	1.08
		(–2.09)	(–0.09)	(1.83)	(3.89)	(4.40)	(3.07)
	$\eta_{e,t}$	0.05	0.16	0.23	0.09	–0.07	–0.18
		(1.58)	(2.80)	(2.56)	(0.91)	(–0.74)	(–1.45)
	$\eta_{d,t}$	–0.05	0.04	0.21	0.36	0.25	0.12
		(–0.97)	(0.47)	(1.87)	(2.47)	(1.65)	(0.60)
		[0.04]	[0.05]	[0.08]	[0.15]	[0.13]	[0.09]
	LR	9.39	4.70	1.06	19.18	24.05	18.59

NOTE: This table reports the ordinary least-squares (OLS) regression results of real fixed nonresidential investment growth on excess stock market return and its three components. Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The adjusted R^2 is reported in brackets. *LR*, the statistic of log-likelihood ratio test of equal coefficients in row 6, has a χ^2 distribution with two degrees of freedom and its critical value at the 5 percent significance level is 5.99. The data are quarterly and span from 1953:Q1 to 1997:Q4 because of the leads in the dependent variable. The decomposition is based on the VAR estimation reported in Table 2. See Appendix A for a description of the data.

explains 8 percent of variations in future investment growth. In row 2, the expected return, $E_{t-1}e_{M,t}$, is negatively correlated with the next two quarters' investment growth and the correlation turns positive as the forecasting horizon increases. Its predictive power concentrates at relatively long horizons and peaks around two to three years, at which it explains about 14 percent of variations in investment growth. As shown in row 3, shocks to the expected future return, $\eta_{e,t}$, also forecast investment growth; however, their predictive patterns are quite different from those of $E_{t-1}e_{M,t}$. In particular, $\eta_{e,t}$ is positively correlated with future investment growth over short horizons and the correlation turns negative as the forecasting horizon increases. Moreover, its predictive power concentrates at relatively short horizons and peaks at two quarters, at which it explains about 7 percent of variations in investment growth. In contrast, row 4 shows that the shock to the dividend, $\eta_{d,t}$, does not contain much information about future investment growth. The correlation between the two is not statistically significant until the forecasting horizon increases to 2 years, and then it becomes insignificant again at longer forecasting horizons. At its peak, $\eta_{d,t}$ explains only 1 percent of variations in the investment growth rate. Moreover, row 5 shows that the total shock, $\eta_{e,t}+\eta_{d,t}$, displays a similar predictive pattern to that of $\eta_{e,t}$. Therefore, the forecasting power of stock market return mainly comes from the expected return and shocks to the expected

Table 5

Forecasting Nondurable Consumption and Service Growth

		Forecast horizon					
Row	Regressor	1	2	4	8	12	16
1	$e_{M,t}$	0.01	0.02	0.04	0.03	0.03	0.02
		(2.60)	(2.56)	(3.27)	(2.14)	(1.83)	(1.10)
		[0.05]	[0.05]	[0.05]	[0.01]	[0.00]	[–0.00]
2	$E_{t-1}e_{M,t}$	0.00	0.02	0.04	0.06	0.01	–0.06
		(0.27)	(0.59)	(0.73)	(0.77)	(0.11)	(–0.58)
		[–0.00]	[0.00]	[0.01]	[0.01]	[–0.01]	[–0.00]
3	$\eta_{e,t}$	0.02	0.03	0.03	0.01	0.03	0.04
		(3.04)	(2.67)	(1.97)	(0.49)	(0.93)	(1.23)
		[0.07]	[0.05]	[0.03]	[–0.00]	[–0.00]	[0.00]
4	$\eta_{d,t}$	–0.01	–0.01	0.02	0.03	0.01	–0.02
		(–0.72)	(–0.68)	(0.94)	(0.71)	(0.24)	(–0.42)
		[–0.00]	[–0.00]	[–0.00]	[–0.00]	[–0.01]	[–0.01]
5	$\eta_{e,t}+\eta_{d,t}$	0.02	0.02	0.04	0.02	0.03	0.04
		(2.76)	(2.51)	(2.66)	(0.96)	(1.14)	(1.26)
		[0.06]	[0.04]	[0.04]	[–0.00]	[0.00]	[0.00]
6	$E_{t-1}e_{M,t}$	0.0	0.02	0.04	0.06	0.01	–0.06
		(0.33)	(0.64)	(0.79)	(0.81)	(0.12)	(–0.58)
	$\eta_{e,t}$	0.02	0.03	0.04	0.02	0.03	0.04
		(2.92)	(2.58)	(2.41)	(0.76)	(1.07)	(1.30)
	$\eta_{d,t}$	0.00	0.00	0.04	0.04	0.03	0.01
		(0.41)	(0.34)	(1.68)	(1.01)	(0.65)	(0.11)
		[0.06]	[0.05]	[0.04]	[0.00]	[–0.01]	[–0.00]
	LR	3.54	1.86	0.04	0.89	0.14	2.18

NOTE: This table reports the ordinary least-squares (OLS) regression results of real nondurable consumption growth, which is measured by (nondurable + service – shoes – clothes), on excess stock market return and its three components. Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The adjusted R^2 is reported in brackets. *LR*, the statistic of log-likelihood ratio test of equal coefficients in row 6, has a χ^2 distribution with two degrees of freedom and its critical value at the 5 percent significance level is 5.99. The data are quarterly and span from 1953:Q1 to 1997:Q4 because of the leads in the dependent variable. The decomposition is based on the VAR estimation reported in Table 2. See Appendix A for a description of the data.

future return, while the information content of dividend shocks is rather limited. These results are not a surprise because dividend shocks account for a relatively small portion of variations in excess stock market returns, as shown in Table 3.

Although excess stock market return and future investment growth are positively correlated at all horizons, the forecasting ability of excess stock market return is considerably compromised because of different predictive patterns between the expected return and shocks to the expected future return. This point is clearly demonstrated in row 6 of Table 4, which shows the multivariate regression results of investment growth on the three components of excess stock market return. I find that the coefficients of the expected return and shocks to the expected future return have opposite signs over both short and long horizons, as in the univariate regressions. Also, the adjusted R^2 in row 6 is much higher than its counterpart in row 1. Moreover, the last line of row 6 reports the log-likelihood ratio test of the null hypothesis that the three components have the same coefficient, which is overwhelmingly rejected in most cases.

To summarize, I find that the dividend shock of excess stock market return provides little information about future investment. Also, the expected return and shocks to the expected future return display quite different predictive patterns. Together, my results suggest that the forecasting power of

Table 6

Forecasting Durable Consumption Growth

Row	Regressor	Forecast horizon 1	2	4	8	12	16
1	$e_{M,t}$	0.13	0.27	0.33	0.19	0.11	0.06
		(3.43)	(5.96)	(4.72)	(3.05)	(1.45)	(0.72)
		[0.09]	[0.19]	[0.12]	[0.02]	[–0.00]	[–0.00]
2	$E_{t-1}e_{M,t}$	0.18	0.43	0.80	1.04	0.77	0.48
		(2.51)	(3.27)	(3.81)	(4.61)	(3.10)	(1.53)
		[0.03]	[0.10]	[0.16]	[0.14]	[0.05]	[0.01]
3	$\eta_{e,t}$	0.12	0.19	0.11	–0.08	–0.08	–0.02
		(2.63)	(4.08)	(2.09)	(–0.99)	(–0.67)	(–0.13)
		[0.05]	[0.07]	[0.01]	[–0.00]	[–0.00]	[–0.01]
4	$\eta_{d,t}$	0.01	0.11	0.33	0.09	–0.01	–0.17
		(0.06)	(1.12)	(2.30)	(0.42)	(–0.08)	(–0.74)
		[–0.01]	[0.00]	[0.02]	[–0.00]	[–0.01]	[–0.00]
5	$\eta_{e,t}+\eta_{d,t}$	0.12	0.23	0.19	–0.06	–0.09	–0.06
		(2.95)	(4.88)	(3.25)	(–0.92)	(–0.79)	(–0.52)
		[0.05]	[0.10]	[0.03]	[–0.00]	[–0.00]	[–0.00]
6	$E_{t-1}e_{M,t}$	0.18	0.43	0.79	1.04	0.76	0.49
		(2.78)	(3.73)	(4.23)	(4.69)	(3.08)	(1.52)
	$\eta_{e,t}$	0.13	0.23	0.17	–0.07	–0.08	–0.04
		(2.98)	(4.74)	(2.89)	(–0.89)	(–0.70)	(–0.30)
	$\eta_{d,t}$	0.07	0.23	0.41	0.04	–0.07	–0.20
		(0.85)	(2.48)	(2.70)	(0.23)	(–0.40)	(–0.93)
		[0.09]	[0.20]	[0.20]	[0.13]	[0.04]	[0.00]
	LR	1.32	4.13	18.52	24.69	9.95	3.64

NOTE: This table reports the ordinary least-squares (OLS) regression results of real durable consumption growth on excess stock market return and its three components. Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The adjusted R^2 is reported in brackets. *LR*, the statistic of log-likelihood ratio test of equal coefficients in row 6, has a χ^2 distribution with two degrees of freedom and its critical value at the 5 percent significance level is 5.99. The data are quarterly and span from 1953:Q1 to 1997:Q4 because of the leads in the dependent variable. The decomposition is based on the VAR estimation reported in Table 2. See Appendix A for a description of the data.

excess stock market return is rather limited, although it is a forward-looking variable.

Nondurable Consumption and Service

Hall (1978) documents a positive relationship between stock price and future consumption (nondurable and service) growth, which is at odds with the permanent income hypothesis. Hall interprets his results as consumption adjusting to capital gain with lags. In row 1 of Table 5, I confirm Hall's results and show that excess stock market return, $e_{M,t}$, forecasts consumption growth up to eight quarters.[9] Its predictive power peaks around four quarters with an adjusted R^2 of about 5 percent. Row 2 shows that the information content of excess stock market return does not come from the expected return, $E_{t-1}e_{M,t}$, which does not forecast consumption growth at any horizons. This finding is consistent with early evidence that consumption is not sensitive to interest rate changes or that the elasticity of inter-temporal substitution is small. Interestingly, dividend shocks, $\eta_{d,t}$, do not explain future consumption growth either, as shown in row 4. Therefore, all the predictive power of excess stock market return comes from shocks to the expected future return, $\eta_{e,t}$. As shown in row 3, $\eta_{e,t}$ forecasts con-

[9] In Table 5, I exclude shoes and clothes from the nondurable consumption.

Table 7

Forecasting Fixed Residential Investment Growth

		Forecast horizon					
Row	Regressor	1	2	4	8	12	16
1	$e_{M,t}$	0.29	0.49	0.55	0.14	0.04	0.06
		(4.55)	(4.49)	(3.69)	(0.64)	(0.24)	(0.37)
		[0.20]	[0.19]	[0.09]	[–0.00]	[–0.01]	[–0.01]
2	$E_{t-1}e_{M,t}$	0.53	1.13	2.00	2.03	1.45	0.77
		(4.69)	(5.93)	(7.12)	(3.14)	(1.89)	(1.07)
		[0.16]	[0.24]	[0.28]	[0.14]	[0.05]	[0.01]
3	$\eta_{e,t}$	0.19	0.25	0.02	–0.45	–0.37	–0.12
		(3.67)	(2.90)	(0.20)	(–2.55)	(–1.34)	(–0.44)
		[0.06]	[0.04]	[–0.01]	[0.02]	[0.01]	[–0.00]
4	$\eta_{d,t}$	0.09	0.15	0.39	0.18	0.03	–0.10
		(0.68)	(0.94)	(1.49)	(0.36)	(0.07)	(–0.23)
		[–0.00]	[–0.00]	[0.00]	[–0.00]	[–0.01]	[–0.01]
5	$\eta_{e,t}+\eta_{d,t}$	0.21	0.30	0.12	–0.42	–0.37	–0.15
		(3.50)	(3.02)	(1.07)	(–3.08)	(–1.58)	(–0.68)
		[0.08]	[0.05]	[–0.00]	[0.01]	[0.01]	[–0.00]
6	$E_{t-1}e_{M,t}$	0.53	1.13	2.00	2.01	1.44	0.76
		(4.84)	(6.17)	(7.55)	(3.12)	(1.86)	(1.07)
	$\eta_{e,t}$	0.22	0.30	0.09	–0.45	–0.38	–0.14
		(3.73)	(2.95)	(0.81)	(–2.92)	(–1.42)	(–0.53)
	$\eta_{d,t}$	0.20	0.29	0.40	–0.09	–0.20	–0.18
		(1.53)	(1.72)	(1.87)	(–0.27)	(–0.64)	(–0.56)
		[0.24]	[0.29]	[0.28]	[0.15]	[0.05]	[0.00]
	LR	10.40	23.96	43.37	31.30	12.87	3.28

NOTE: This table reports the ordinary least-squares (OLS) regression results of real fixed residential investment growth on excess stock market return and its three components. Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The adjusted R^2 is reported in brackets. *LR*, the statistic of log-likelihood ratio test of equal coefficients in row 6, has a χ^2 distribution with two degrees of freedom and its critical value at the 5 percent significance level is 5.99. The data are quarterly and span from 1953:Q1 to 1997:Q4 because of the leads in the dependent variable. The decomposition is based on the VAR estimation reported in Table 2. See Appendix A for a description of the data.

sumption growth up to four quarters. The associated adjusted R^2 peaks at a one-quarter horizon, indicating that consumption actually reacts to capital gain/loss quickly. Again, the total shock, $\eta_{e,t}+\eta_{d,t}$, exhibits very similar predictive patterns to those of $\eta_{e,t}$.

Consumption reacts differently to $\eta_{d,t}$ and $\eta_{e,t}$ for two possible reasons. First, dividend shocks account for a relatively small portion of variations in excess stock market return, as reported in Table 3. Second, Table 4 also shows that $\eta_{e,t}$ has a much larger standard error than $\eta_{d,t}$ has. In other words, there is greater uncertainty associated with shocks to the expected future return than with shocks to dividends. As a result, consumers react with more caution to $\eta_{e,t}$ than to $\eta_{d,t}$. Consistent with the second hypothesis, I find that consumption reacts contemporaneously to dividend shocks, but not shocks to the expected return. Another interesting observation is that, unlike nonresidential investment, row 6 shows that the adjusted R^2 in the multivariate regressions is not substantially higher than its counterpart in row 1. Also, the null hypothesis that the three components have the same coefficient is not rejected by the log-likelihood ratio test in any cases.

Durable Consumption and Fixed Residential Investment

Table 6 reports the regression results of durable consumption. Excess stock market return, $e_{M,t}$, is

Table 8

Forecasting GDP Growth

Row	Regressor	Forecast horizon 1	2	4	8	12	16
1	$e_{M,t}$	1.03	0.08	0.12	0.09	0.07	0.05
		(3.21)	(4.09)	(4.36)	(3.41)	(2.60)	(1.66)
		[0.07]	[0.14]	[0.13]	[0.03]	[0.01]	[0.00]
2	$E_{t-1}e_{M,t}$	1.04	0.12	0.27	0.35	0.32	0.27
		(1.76)	(2.46)	(3.27)	(3.48)	(3.01)	(2.45)
		[0.02]	[0.07]	[0.16]	[0.14]	[0.08]	[0.05]
3	$\eta_{e,t}$	0.03	0.05	0.04	–0.02	–0.03	–0.03
		(2.35)	(2.82)	(1.97)	(–0.72)	(–0.70)	(–0.73)
		[0.04]	[0.05]	[0.01]	[–0.00]	[–0.00]	[–0.00]
4	$\eta_{d,t}$	0.00	0.04	0.11	0.12	0.09	0.07
		(0.15)	(1.19)	(2.87)	(1.87)	(1.64)	(0.83)
		[–0.01]	[0.00]	[0.02]	[0.01]	[0.00]	[–0.00]
5	$\eta_{e,t}+\eta_{d,t}$	0.03	0.07	0.07	0.01	–0.01	–0.02
		(2.67)	(3.55)	(2.92)	(0.27)	(–0.19)	(–0.43)
		[0.04]	[0.08]	[0.03]	[–0.01]	[–0.01]	[–0.01]
6	$E_{t-1}e_{M,t}$	0.04	0.12	0.27	0.35	0.32	0.27
		(1.88)	(2.65)	(3.51)	(3.73)	(3.16)	(2.49)
	$\eta_{e,t}$	0.03	0.07	0.06	–0.00	–0.02	–0.02
		(2.63)	(3.30)	(2.56)	(–0.13)	(–0.39)	(–0.53)
	$\eta_{d,t}$	0.02	0.08	0.14	0.12	0.08	0.05
		(1.06)	(2.57)	(3.49)	(2.13)	(1.58)	(0.74)
		[0.06]	[0.15]	[0.20]	[0.15]	[0.08]	[0.04]
	LR	0.66	2.65	17.13	24.31	14.52	8.84

NOTE: This table reports the ordinary least-squares (OLS) regression results of real GDP growth on excess stock market return and its three components. Newey-West (1987) corrected standard errors are used to calculate the t statistics, which are reported in parentheses. The adjusted R^2 is reported in brackets. *LR*, the statistic of log-likelihood ratio test of equal coefficients in row 6, has a χ^2 distribution with two degrees of freedom and its critical value at the 5 percent significance level is 5.99. The data are quarterly and span from 1953:Q1 to 1997:Q4 because of the leads in the dependent variable. The decomposition is based on the VAR estimation reported in Table 2. See Appendix A for a description of the data.

positively correlated with the future durable consumption growth at all horizons. However, its forecasting power concentrates over relatively short horizons and peaks at two quarters with an adjusted R^2 of 19 percent. The predictive pattern is also quite different among its three components. The expected return, $E_{t-1}e_{M,t}$, is positively correlated with future durable consumption growth at all horizons, and its forecasting power peaks at one year with an adjusted R^2 of 16 percent. In contrast, shocks to the expected future return, $\eta_{e,t}$, are positively correlated with future durable consumption over short horizons and the correlation turns negative as the horizon increases. Their predictive power peaks at two quarters with an adjusted R^2 of 7 percent. Again, I find that the forecasting power of dividend shocks, $\eta_{d,t}$, is rather limited: It peaks around one year with an adjusted R^2 of 1 percent. Also, the forecasting power of total shocks $\eta_{e,t} + \eta_{d,t}$ displays similar patterns to those of $\eta_{e,t}$. Because of their different predictive patterns, row 6 shows that the joint forecasting power of the three components of excess stock market return is larger than its counterpart in row 1, especially over long horizons. Also, the null hypothesis that the three components have the same coefficient is overwhelmingly rejected in many cases. Table 7 reports the regression results of fixed residential investment, which are qualitatively similar to those of durable consumption, as reported in Table 6 (although it is not discussed in detail here).

To summarize, I find that durable consumption and fixed residential investment show many similarities to fixed nonresidential investment. This finding is not a surprise because durable consumption and fixed residential investment can be thought of as investment in home productions. However, there is one notable difference. It is well known that durable consumption and fixed residential investment tend to lead fixed nonresidential investment. Gomme, Kydland, and Rupert (2001) have emphasized this feature of the data in business cycle modeling. In my paper, this is reflected by the fact that durable consumption and fixed residential investment tend to respond to excess stock market return and its components much faster than fixed nonresidential investment does.

GDP

Table 8 reports the regression results of GDP. Excess stock market return, $e_{M,t}$, is positively correlated with future GDP growth over all horizons, and its predictive power peaks at two quarters with an adjusted R^2 of 14 percent. Its components, however, display quite different predictive patterns. The expected return, $E_{t-1}e_{M,t}$, is also positively correlated with future GDP growth at all horizons, and its predictive power peaks at two years with an adjusted R^2 of 16 percent. In contrast, shocks to the expected future return, $\eta_{e,t}$, are positively correlated with future GDP growth at short horizons and the correlation turns negative as forecasting horizons increase. Their predictive power peaks at two quarters with an adjusted R^2 of 5 percent. Interestingly, dividend shocks are always positively correlated with future GDP growth; however, their predictive power is weak, as I find for the GDP components above. Not surprisingly, row 6 shows that the joint predictive power of the three components is much stronger than its counterpart in row 1, especially over long horizons. Also, the null hypothesis that the three components have the same coefficient is rejected in many cases.

CONCLUSION

In this paper, I first summarize recent evidence against the random walk hypothesis of stock price. Using post-World War II data, I find that over 20 percent of variations in quarterly excess stock market return are explained by past stock market variance and other informational variables. I then analyze the predictive power of excess stock market return for economic activities by decomposing it into three parts: expected return, shocks to the expected future return, and shocks to the expected future dividend. I find that stock price is not sensitive to dividend news, and, therefore, the dividend component has little predictive power for GDP and its components. In contrast, the expected return and shocks to the expected future return, especially the former, are strong predictors for economic activities. However, their predictive patterns are quite different, especially over long horizons. Together, my results explain why the predictive power of stock market returns is rather limited.

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Appendix A

DATA DESCRIPTION

Stock Market Return and Its Forecasting Variables

Consumption-Wealth Ratio: cay_t

Source: <www.newyorkfed.org/rmaghome/economist/lettau/data.html>.

S&P 500 Dividend Yield: dp_t

Last four-quarter dividends divided by stock price using S&P 500 stocks. Source: Haver Analytics (2001).

Stochastically Detrended Risk-Free Rate: $rrel_t$

Risk-free rate less its last four-quarter average or

$$rrel_t = r_{f,t} - \frac{1}{4}\sum_{k=1}^{4} r_{f,t-k},$$

where $r_{f,t}$ is the nominal risk-free rate. I construct the quarterly nominal risk-free rate by summing up the monthly rate within each quarter. Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago, 2002. Used with permission. All rights reserved. <www.crsp.uchicago.edu>.

Excess Stock Market Return: $e_{M,t}$

Value-weighted stock market return less the nominal risk-free rate. Source: CRSP.

Stock Market Variance: $\sigma_{M,t}$

Sum of the squared deviation of daily excess stock market return for its quarterly average, or

$$\sigma_{M,t} = \sum_{j=1}^{\tau} (e_{M,t\tau} - \bar{e}_{M,\tau})^2,$$

where $e_{M,t\tau}$ is the daily excess stock market return and $\bar{e}_{M,t}$ is its average in quarter t. The daily risk-free rate is assumed to be equal to the monthly rate divided by the number of trading days. Source: I use the daily market return constructed by Schwert (1990) before July 2, 1962, and use the daily value-weighted market return (VWRET) from CRSP thereafter; the nominal monthly risk-free rate is also from CRSP. Following Campbell et al. (2001), I downweight stock market variance during the 1987 stock market crash.

National Accounts Data

Source: Bureau of Economic Analysis.

Appendix B

DERIVATION OF THE SHOCK TO THE EXPECTED FUTURE RETURN

From equation (8), it is straightforward to show that

(B1) $$E_t X_{t+j} = A + BA + \cdots + B^{j-1}A + B^j X_t,$$

and

(B2) $$E_{t-1}X_{t+j} = A + BA + \cdots + B^j A + B^{j+1}X_{t-1}.$$

Then

(B3) $$\begin{aligned} &-(E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j X_{t+j} \\ &= -\sum_{j=1}^{\infty}\rho^j[A + BA + \cdots + B^{j-1}A + B^j X_t - A - BA - \cdots - B^j A - B^{j+1}X_{t-1}] \\ &= -\sum_{j=1}^{\infty}\rho^j[B^j(X_t - X_{t-1}) - B^j A] \\ &= -\sum_{j=1}^{\infty}\rho^j[B^j A + B^j\varepsilon_t - B^j A] \\ &= -\rho B(I - \rho B)^{-1}\varepsilon_t. \end{aligned}$$

Because $e_{M,t}$ is the first row of X_t,

(B4) $$\begin{aligned} &-(E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j e_{M,t+j} \\ &= -e1'(E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j X_{t+j} \\ &= -e1'\rho B(I - \rho B)^{-1}\varepsilon_t. \end{aligned}$$

Why the Fed Should Ignore the Stock Market

James B. Bullard and Eric Schaling

INTRODUCTION

Equity Prices and Monetary Policy Rules

The dramatic movements in equity prices in the United States during the last decade or so have focused considerable attention on stock markets as a barometer of economic well-being. Separately, there has been growing interest in the use of nominal interest rate feedback rules for the conduct of monetary policy since the publication of Taylor (1993).[1] These two developments have led to a debate over whether equity prices possibly belong in a policy rule of the type that Taylor recommended. One way to pose this question is to ask, "Should monetary policymakers using Taylor-type rules include in the rule a reaction to movements in the level of equity prices?"[2] Another way to pose this question is to use the language that a variable included in a reaction function of the policy authority is a "target" variable. Then we can ask, somewhat more provocatively, "Should monetary policymakers target the level of equity prices?"[3]

As an empirical matter, Rigobon and Sack (2001) report that the Federal Reserve does in fact react to changes in stock market valuations when adjusting its instrument, the intended nominal federal funds rate. The main finding of Rigobon and Sack is that an increase of 5 percent in the value of the Standard & Poor's 500 stock index raises the probability of a 25-basis-point increase in the intended federal funds rate by about one half. Their findings are symmetric with respect to a decrease in the level of equity prices. According to these results, then, if the probability of a decision to raise the intended federal funds rate by 25 basis points had been 20 percent and the S&P 500 unexpectedly increased by 5 percent, the probability of the decision to raise the rate would rise to 70 percent. Thus the Federal Reserve does appear to react to movements in stock market valuations with some vigor.

We study a simple, small dynamic model of the U.S. macroeconomy suggested by Woodford (1999). We follow Rotemberg and Woodford (1998) in examining the consequences of Taylor-type monetary policy rules in this context. The first rule we consider is similar to Taylor's (1993) original rule and does not involve adjusting the nominal interest rate in response to equity price movements. A second rule we consider is exactly like the first, but with an additional term which describes the monetary authority's reaction to stock prices. We are interested in ascertaining, in some generality, how the economy would perform under the second rule as opposed to how it would perform under the first rule.

Main Results

Our main finding is that adding equity prices to the policymaker's Taylor-type rule and leaving all else constant, in general, will not improve economic performance and might possibly do considerable harm, relative to a policy of simply ignoring fluctuations in equity prices altogether. We also find that if policymakers place substantial weight on the asset price component of their policy rule, leaving all else constant, they will encounter indeterminacy of rational expectations equilibrium. Actual macroeconomic outcomes would then be unpredictable because of the multiplicity of equilibria. Finally, we note that an alternative interpretation of our findings suggests a certain *irrelevance* of whether equity prices are included in the policy rule.[4]

James B. Bullard is an assistant vice president and economist at the Federal Reserve Bank of St. Louis. Eric Schaling is a professor of economics at Rand Afrikaans University and thanks the Reserve Bank staff for their hospitality. The authors also thank Hui Guo, Frank Schmid, and Robert Rasche for helpful comments. Charles Hokayem provided research assistance.

1 For an introduction to Taylor-type monetary policy rules, see Taylor (1999).

2 Taylor rules are normally viewed as applying to questions of business cycle fluctuations and the associated stabilization policy. In the event of a financial crisis, the Fed does watch equity price developments closely and has at times provided substantial liquidity to markets. We do not consider financial crises in this paper.

3 Svensson (2002) argues for the language that "target" variables are those that appear in loss functions and not necessarily those in reaction functions. We have no quarrel with this in general. In this paper, however, we discuss issues that are prior to the specification of a loss function for the monetary authority. In addition, our results may be easily interpreted if we think of the authorities who include equity prices in the policy rule as "targeting" the level of equity prices.

4 We will show that, in this model, an increase in the weight policymakers place on equity prices in the policy rule could be accompanied by increases in the weights placed on inflation deviations and the output gap, such that ultimately the policy rule is unchanged.

The intuition behind our main finding is compelling and may be quite general. In models like the one we study, policymakers are using their influence over an asset return—a short-term nominal interest rate—in order to try to minimize inflation and output variability. Financial markets in the model are closely linked by arbitrage relationships. By including additional asset prices—equity prices—in the policy rule, policymakers are in effect saying that they will use their influence over one asset price to help control or "target" other asset prices. But, due to arbitrage in financial markets, any movements in short-term nominal interest rates actually *add* to the volatility of these other asset prices, even as they may be necessary to stabilize inflation and output. Thus, while the inflation and output components of the Taylor-type policy rule call for the policy authority to move the short-term nominal interest rate around in response to events, this actually *conflicts* with the effect of the equity price component of the policy rule, which calls for the policy authority to keep the short-term nominal interest rate relatively constant. In the limiting case where all the weight in the policy rule is on the equity price component, the policy rule we derive calls for an interest rate peg—that is, no movement in short-term nominal interest rates whatsoever! An interest-rate-peg policy produces indeterminacy of rational expectations equilibrium in the model we analyze here and is known to produce indeterminacy in a host of closely related models. Viewed from this perspective, it does not appear that including equity prices in a monetary policy rule is to be recommended.

Recent Related Literature

Bernanke and Gertler (1999, 2001) use a model with a financial market friction that produces a "financial accelerator," a mechanism that magnifies the effects of exogenous shocks. They calibrate their model, including a stochastic process for exogenous "nonfundamental" shocks to equity returns, and use the results of simulations to argue that there is little or no gain from including equity prices in the Taylor-type policy rule of the monetary authority. Bernanke and Gertler (1999, 2001) take the position that reactions to equity price movements are warranted only to the extent that they contain information concerning expected inflation.

Cecchetti et al. (2000) use a methodology similar to Bernanke and Gertler (1999, 2001), and, in fact, at times simulate the same model as Bernanke and Gertler. But Cecchetti et al. (2000) conclude that central banks could derive some benefit from including significant reactions to asset price movements when making monetary policy. Bernanke and Gertler (2001, p. 257) comment on the divergent findings, saying that while the models used are much the same, the nature of the shock process for nonfundamental stock prices is significantly different. In effect, Cecchetti et al. (2000) assume that the policymaker knows with certainty that observed stock price movements are not fundamental in nature and, importantly, when the exogenous bubble is going to burst. With this knowledge in hand, the policymaker can improve economic performance by reacting to stock price movements. Bernanke and Gertler (2001) suggest that these conditions are unlikely to be met in actual economies.

The present paper differs from the Bernanke and Gertler (1999, 2001) line of research in several ways. While the model we use here is essentially very similar, we abstract from any credit market frictions inducing "financial accelerator" effects and concentrate instead on what standard models have to say about asset market arbitrage relationships. We are able to isolate some analytic conditions that we think are quite revealing about the nature of policy regimes which include reactions to equity prices. Our results are not dependent on a particular calibration of the economy we study. And our results do not depend on the idea that there are movements in asset prices which are of unknown origin from the perspective of the model.

Goodhart (2000) suggests that better monetary policy performance might result if policymakers used broader measures of inflation that include a more explicit account of the prices of assets such as housing and equities. Goodhart's (2000) logic is based on work by Alchian and Klein (1973). In a survey of this issue, Filardo (2000) finds that U.S. economic performance would probably not be enhanced by a switch to such inflation measures.

Bordo and Jeanne (2001) employ a simple dynamic model somewhat different from the one used in this paper. Their model includes collateral constraints. If the economy has an uncertain trend rate of growth, then the value of the assets in the model will fall sharply in value once news arrives that a lower trend rate of growth is likely. This event then has further effects in financial markets because the value of the economy's collateral has been diminished. In the present paper, we abstract from collateral constraints.

Whether the Federal Reserve should respond aggressively to movements in equity prices has also been debated less formally. The current conventional wisdom in the United States, as reflected in a great deal of financial market commentary, seems to be that movements in stock prices "provide information" on the state of the economy that is not otherwise available, so that the central bank properly reacts to equity price movements by adjusting its short-term nominal interest rate target. In this connection there has been considerable discussion of a wealth effect on consumption of higher levels of stock prices. However, there is an older, currently less popular, conventional wisdom that asserts that central banks would be "looking in the mirror" if they attempted to react to equity price movements. This view emphasizes asset market linkages and stresses that stock market investors do not have any private information that is not available to the central bank. Our results can be viewed as a formalization of this older conventional wisdom.

ENVIRONMENT

Aggregate Relationships

Rotemberg and Woodford (1999) analyze an economy characterized by a continuum of households maximizing utility over an infinite horizon, in which utility is defined over consumption and the disutility of production. Each household produces a single differentiated good, but consumes a Dixit-Stiglitz aggregate of all goods produced in the economy. Output is sold at a utility-maximizing price under the "sticky price" constraint that only a fraction of the goods prices may be changed in any given period and that other prices must be left at their previous period values. The solution of the households' problem, suitably linearized and simplified as in Woodford (1999), dictates equations (1) and (3) below which describe how output and inflation evolve in this economy. The first equation is given by

$$z_t^d = E_t z_{t+1}^d - \sigma^{-1}\left[r_t^d - E_t \pi_{t+1}^d\right] + \sigma^{-1} r_t^n, \tag{1}$$

where π_t^d is the deviation of the inflation rate from a target value π^*, z_t^d is the output gap at t, r_t^d is the deviation of the short-term nominal interest rate from a target value r^*, $\sigma > 0$ is a parameter related to the intertemporal elasticity of substitution in the households' problem, and r_t^n is a shock term that follows an AR(1) process

$$r_t^n = \alpha r_{t-1}^n + \omega_t, \tag{2}$$

where $0 < \alpha < 1$ is white noise. Inflation is determined according to

$$\pi_t^d = \kappa z_t^d + \beta E_t \pi_{t+1}^d, \tag{3}$$

where $\kappa > 0$ relates to the degree of price stickiness in the economy and $0 < \beta < 1$ is the common household discount factor.

We close the model with a Taylor-type policy rule:

$$r_t^d = \gamma_\pi \pi_t^d + \gamma_z z_t^d, \tag{4}$$

where $\gamma_\pi > 0$ and $\gamma_z > 0$ are parameters chosen by the monetary authority. This particular policy rule has the nominal interest rate reacting to current-period values of inflation and output deviations and is the most commonly studied rule. We could also comment on our results under many other assumptions about the nature of this rule, such as the case where the policy authority reacts to lagged values of output and inflation deviations. Generally, however, the exact nature of this Taylor-type rule is not crucial for the points we make in this paper, and so we just use equation (4).

We assume rational expectations.

Equity Prices

We wish to understand the consequences of policymakers using a rule of the form of equation (4), but with the percentage deviation of equity prices from a rationally priced benchmark included. To do so, we must first define an equity price consistent with the Rotemberg and Woodford (1999) microfoundations.

In the Rotemberg and Woodford (1998) framework, as in many dynamic stochastic general equilibrium frameworks, arbitrage relationships can be used to price any asset that might be held by households in the model, thanks in part to their assumption that financial markets are complete.[5] This means that a financial claim to a random nominal quantity X_T has value at t of $E_t[\delta_{t,T} X_T]$, where $\delta_{t,T}$ is the stochastic discount factor given by

$$\delta_{t,T} = \frac{\beta u'(C_T)}{u'(C_t)} \tag{5}$$

[5] Also see Rouwenhorst (1995) for a discussion of asset pricing in dynamic stochastic general equilibrium models.

and where $u(C_t)$ is the common period utility function of a household. The gross nominal interest rate on a nominal one-period bond is then given by

$$(6) \qquad R_t = E_t\left[\delta_{t,t+1}\right]^{-1}$$

as in Rotemberg and Woodford (1998, p. 12).

Since the stochastic discount factor prices all assets in this model, let us denote the price of a share of aggregate equity by p_t and note that $p_t = 1/R_t$. Rotemberg and Woodford define the short-term nominal interest rate r_t as $r_t = \ln R_t$. We note that

$$(7) \qquad \ln R_t = \ln 1 - \ln p_t = -\ln p_t \ .$$

We conclude that

$$(8) \qquad r_t = -\ln p_t$$

and that, when the nominal interest rate is at the target value r^*, the price of a share of aggregate equity must be at a corresponding long-run equilibrium level denoted by p^*, with the relationship between the two given by

$$(9) \qquad r^* = -\ln p^* \ .$$

A Policy Rule with Equity Prices

We now assume that policymakers wish to include the percentage deviation of the general level of equity prices from the long-run equilibrium level in their policy reaction function. Thus they wish to adjust nominal interest rates in reaction to

$$(10) \qquad \frac{p_t - p^*}{p^*} \approx \ln p_t - \ln p^* \ .$$

The form of the policy rule we wish to study is therefore

$$(11) \qquad r_t^d = \gamma_\pi \pi_t^d + \gamma_z z_t^d + \gamma_a (\ln p_t - \ln p^*)$$

with $\gamma_a \geq 0$. Importantly, equation (11) can be rewritten as follows:

$$(12) \qquad r_t - r^* = \gamma_\pi \pi_t^d + \gamma_z z_t^d - \gamma_a (r_t - r^*)$$

or

$$(13) \qquad r_t - r^* = \frac{\gamma_\pi}{1+\gamma_a}\left(\pi_t - \pi^*\right) + \frac{\gamma_z}{1+\gamma_a}\left(z_t - z^*\right) \ .$$

If we set $\gamma_a = 0$, then the rule collapses to the one described by equation (4). Thus we see that the central bank wishing to target the deviation of the level of equity prices from a long-run equilibrium can be viewed as a central bank that uses an ordinary Taylor-type rule in which the coefficients of the original Taylor rule have been reduced by a factor of $1 + \gamma_a$

Of course in deriving the modified policy rule equation (13), we have relied heavily on the arbitrage relationships that are assumed to exist in this model and that drive asset pricing in many models of this type. We think this is a logical first step in trying to understand the implications of equity price movements for monetary policy.[6]

We now turn to drawing out the implications of this finding for the conduct of monetary policy.

Main Results

The model given by equations (1), (2), (3), and (13) can be viewed as the same one that has been studied by Woodford (1999) and Bullard and Mitra (2002),[7] provided one relates the Bullard and Mitra Taylor rule coefficients φ_π and φ_z to the Taylor rule coefficients in equation (13) via

$$(14) \qquad \varphi_\pi = \frac{\gamma_\pi}{1+\gamma_a}$$

and

$$(15) \qquad \varphi_z = \frac{\gamma_z}{1+\gamma_a} \ .$$

Of course, since γ_a enters equation (13) in such a simple way, it is perhaps easiest to just remember that as the value of γ_a increases, it tends to drive the coefficients on inflation deviations and the output gap to zero in the Taylor rule and otherwise leave the model specification unaffected. We will thus simply import some results from Bullard and Mitra (2002) to discuss and then provide an analysis of the consequences of lower values for their φ_π and φ_z coefficients in that analysis.

One of the first questions we would like to ask about this model is under what conditions a unique rational expectations equilibrium exists. We can write the system as

$$(16) \qquad y_t = \alpha + B y_{t+1}^e + \chi r_t^n \ ,$$

[6] It is well known that the class of models we are considering do not explain equity price movements very well; on the other hand, how to adequately explain equity price movements is a particularly vexing open question in financial economics. In addition, it strikes us as unwise to design monetary policy rules that call for the monetary authority to react to the component of equity price movements that is unexplained by current theory.

[7] See their sections on contemporaneous data rules.

where $y_t = [z_t, \pi_t]', \alpha = 0$,

$$(17) \qquad B = \frac{1}{\sigma + \varphi_z + \kappa\varphi_\pi}\begin{bmatrix} \sigma & 1-\beta\varphi_\pi \\ \kappa\sigma & \kappa + \beta(\sigma + \varphi_z) \end{bmatrix},$$

and where the form of χ is omitted since it is not needed in what follows. Both z_t and π_t are free variables in this system, and as a result both of the eigenvalues of B must be inside the unit circle for a unique, or determinate, rational expectations equilibrium to exist. Otherwise, the equilibrium will be indeterminate. Bullard and Mitra (2002) show that the necessary and sufficient condition for determinacy is[8]

$$(18) \qquad \kappa(\varphi_\pi - 1) + (1-\beta)\varphi_z > 0 .$$

When condition (18) fails, equilibrium is indeterminate. Bullard and Mitra (2002) also show that when condition (18) is met, the rational expectations equilibrium is learnable in a specific sense.[9]

Using equations (14) and (15) we can rewrite condition (18) as

$$(19) \qquad \kappa\left(\frac{\gamma_\pi}{1+\gamma_a} - 1\right) + (1-\beta)\frac{\gamma_z}{1+\gamma_a} > 0 .$$

This condition is a statement of the Taylor principle, as discussed by Bullard and Mitra (2002) and by Woodford (2001). Since (i) $0 < \beta < 1$ can be interpreted as the common discount factor of the households in the model and (ii) $\kappa > 0$, we can conclude that, for fixed values of γ_a, determinacy will obtain provided the coefficient γ_π is sufficiently large. In particular, if $\gamma_a = \gamma_z = 0$, then the condition is simply that $\gamma_\pi > 1$. That is, the nominal interest rate must be adjusted more than one-for-one with deviations of inflation from target in order for a determinate rational expectations equilibrium to exist. The consequence of setting a lower value for γ_π is that the rational expectations equilibrium is indeterminate.

Now consider fixed values of γ_π and γ_z and suppose the monetary authority wishes to begin including a reaction to equity price movements in its policy rule by setting $\gamma_a > 0$. Such a policy clearly works against satisfaction of condition (19), in that a large enough value of γ_a—enough emphasis by the monetary authority on reacting to equity price movements—will cause condition (19) to fail and indeterminacy to arise.

Condition (19) also suggests that as $\gamma_a \rightarrow \infty$ with all else constant, indeterminacy will occur without question. Thus, as the weight in the policy rule on asset prices gets very large relative to the weight on inflation deviations and the output gap, indeterminacy is ensured. Another look at equation (13) can help the interpretation of this finding. In the situation where $\gamma_a \rightarrow \infty$ with all else constant, the monetary authority is following an interest rate peg—there is no reaction to inflation deviations or the output gap at all. The intuition behind this result is very clear. A very large value of γ_a means that the policy authority wishes to target the level of asset prices much more than it wishes to stabilize inflation and output. The way to keep asset prices relatively constant, given arbitrage relationships, is to keep the short-term interest rate relatively constant. A very large value of γ_a inducing an interest rate peg is just the extreme form of this logic.

There is another, perhaps brighter, interpretation of these results. Typically, parameters such as κ and β have been regarded as part of the preferences and technology underlying the economy, and thus beyond the scope of influence of the monetary authority. The parameters γ_π, γ_z, and γ_a, however, can be set by the central bank. So long as these parameters are chosen to satisfy condition (19), the economy will possess a determinate rational expectations equilibrium. There are obviously many combinations of these parameters that will satisfy this condition. Among these possibilities, some will induce better economic performance than others, according to any criterion that the monetary authority might wish to adopt. Rotemberg and Woodford (1999) discuss in great detail optimal policy rules in this class of simple linear Taylor rules for this model, based on a variety of possible criteria, including the utility of a representative household.

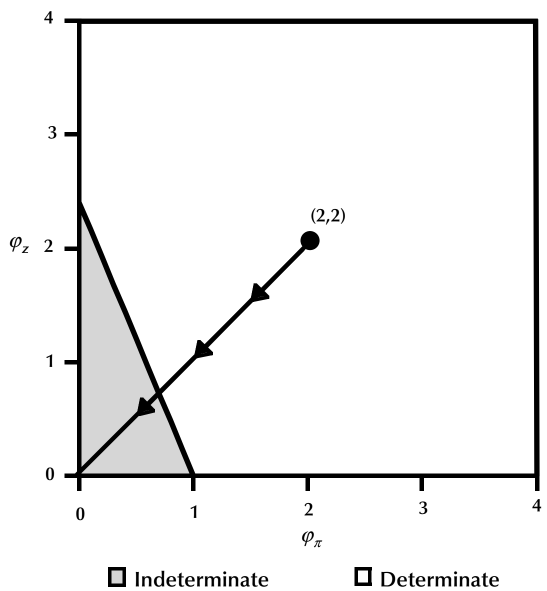
But now consider equation (13) in the context of optimal policy. The monetary authority actually needs to choose only two coefficients, the one on inflation deviations and the one on the output gap, even though they have three parameters, namely γ_π, γ_z, and γ_a, with which to adjust these coefficients. Thus any given value of γ_a *could* be associated with the *optimal* policy in this class of policy rules, provided the policy authority is willing to set γ_π and γ_z appropriately to achieve the optimal coefficients on inflation deviations and the output gap. Thus if we ask, "Could the optimal monetary policy involve an explicit reaction to the level of asset prices in this economy?" the answer is actually, "Yes, it could."

[8] Provided $\kappa(\varphi_\pi - 1) + (1-\beta)\varphi_z \neq 0$.

[9] See Bullard and Mitra (2002) for details.

Figure 1

The Effects of Including Equity Prices in a Taylor Rule



NOTE: As the weight placed on $\gamma_a \to \infty$, any given policy rule shrinks toward the origin in the diagram, which is associated with an interest rate peg. This region is also associated with indeterminacy.

We conclude that it is not quite valid to think that a central bank that is reacting strongly to equity price movements is necessarily following the wrong policy.

However, we think the spirit of the discussion concerning equity prices and monetary policy rules has been one where the responses to inflation deviations and the output gap (i.e., γ_π and γ_z) are considered fixed, and the question is whether any policy improvements could be made by adding a response to equity price movements. Thus it is probably better to think of setting values of γ_a while leaving values of γ_π and γ_z constant. If γ_π and γ_z were already set to optimal values with $\gamma_a = 0$, then moving $\gamma_a = 0$ to a positive value is only going to degrade economic performance. And a large enough value of γ_a could do real damage by creating indeterminacy.

Figure 1 shows a schematic diagram considering condition (19) in conjunction with values of $\gamma_a \geq 0$, using calibrated values of parameters other than φ_π and φ_z from Woodford (1999). We can think of a particular policy rule as a point in Figure 1, such as $(\varphi_\pi, \varphi_z) = (2{,}2)$. These values would induce a determinate rational expectations equilibrium. Now let's suppose the policy authority begins to increase γ_a, leaving all else constant. As we have seen, this reduces the values of φ_π and φ_z toward zero at an equal rate. For large enough values, this would send the economy into the indeterminate region.

CONCLUSION

We have provided a simple analysis of the consequences of including the general level of equity prices in a Taylor-type policy rule. Our analysis differs from most of this literature in that we have emphasized the general equilibrium nature of models in this class and the arbitrage relationships that underpin their microfoundations. Under our preferred interpretation, we find that including equity prices in a Taylor-type policy rule will degrade economic performance and can do real damage by creating indeterminacy of rational expectations equilibrium where such indeterminacy did not otherwise exist. A more benign interpretation suggests that including equity prices in the policy authority's reaction function is essentially irrelevant to achieving optimal monetary policy within this class of rules. These findings are certainly stark, but we think that forces of the type we describe are at work even in more elaborate general equilibrium economies.

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The Monetary Policy Innovation Paradox in VARs: A "Discrete" Explanation

Michael J. Dueker

Empirical studies in macroeconomics—according to Stock and Watson (2001)—focus on one or more of the following: (i) describing macroeconomic data, (ii) forecasting macroeconomic data, (iii) quantifying the sources of macroeconomic fluctuations, and (iv) providing analysis of monetary or fiscal policy. Starting with Sims (1980), the vector autoregression (VAR) has played an important role in all four of these interrelated empirical exercises. Assessing policy and the sources of fluctuations involves careful interpretation of a VAR's forecast errors. Consequently, any alteration of the forecasting information set affects the results of policy analysis to the extent to which the forecast errors change. The empirical exercise in this article augments the forecasting information set and investigates whether the conclusions about monetary policy remain the same. In particular, this article suggests that VAR models ought to consider, when specifying the forecasting equations, how monetary policy is implemented through discrete interest rate changes. I find that the mis-specification of the data-generating process for the federal funds rate significantly affects inferences regarding policymakers' behavior in VAR models.

In this sense, this article is similar to Croushore and Evans (2000), which compares VAR analyses of monetary policy using vintage and real-time data in alternative forecast information sets. Their basic finding is that the conclusions concerning monetary policy are quite robust across these two information sets. Although the change in the forecasting information set that I introduce to the VAR is quite modest in comparison with Croushore and Evans's (2000) real-time data, it is sufficient to resolve one nettlesome puzzle in previous VAR analysis of monetary policy: how policymakers are thought to proceed after they introduce a policy "innovation." The term policy innovation refers to a surprise change in the federal funds rate that is not part of a systematic response—as implied by the VAR coefficients—to the state of the economy. For some sample periods and methods of decomposing forecast errors into separate shocks—enough cases to constitute a pattern—monetary policy shocks derived from VARs suggest that policymakers respond to a policy innovation by following it with additional policy moves in the same direction.

It is natural to ask why policymakers would systematically react to their own unexpected—and perhaps uncalled for—increase in the federal funds rate with further increases.[1] We can call this puzzling pattern the "policy innovation paradox." Specifically, the policy innovation paradox appears in the impulse response function of the federal funds rate to a shock to itself. Under the usual assumption that the federal funds rate is set by monetary policymakers, this impulse response function shows the typical response of monetary policymakers to a shock that they themselves induced. The policy innovation paradox appears when this impulse response continues upward for one or more periods after the initial shock before decaying toward zero. If this characterization of policymaker behavior is accurate, it raises a question: What good does it do for policymakers to systematically follow a surprise increase in the federal funds rate with additional increases? These additional increases would not have a surprise element, nor would they be part of a response to other developments in the economy. The policy innovation paradox would amount to an odd custom of monetary policymakers piling additional funds rate increases on top of a surprise increase.

One rather intricate explanation for this seemingly counterintuitive behavior is that policymakers have access to forecasts that are superior to VAR forecasts. It is possible that the VAR model does not characterize enough policy actions as being systematic responses to developments in the economy. What the model calls a policy innovation may actually be a systematic policy response to an inflation threat that VAR forecasts fail to detect. If such an inflation threat only gradually recedes, policymakers

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[1] Note that when one traces the effect of a monetary policy shock for many periods—48, for example—visual evidence of this phenomenon in the first three or so periods may be difficult to detect in a chart.

might undertake a series of tightening moves to counter it. In the case where the inflation threat goes undetected by the VAR forecasts, the series of tightening policy moves are attributed to an initial policy innovation that is compounded with additional policy moves in the same direction as the innovation. One glaring weakness with this explanation is that the VAR would have to make systematic forecast errors to miss such an inflation threat repeatedly. For this reason, I investigate an alternative explanation in this article.

The idea that policymakers have information beyond what is contained in VAR forecasts also appears in explanations of the "price puzzle." This puzzle arises when an identified VAR suggests that an unexpected tightening of monetary policy leads to an increase in the price level. Many VARs that decompose forecast errors and derive a monetary policy shock exhibit a price puzzle. The generally accepted explanation for the price puzzle is that monetary policymakers can foresee a rise in inflation, causing them to raise interest rates preemptively. When the VAR forecasts fail to predict this rise in inflation, however, the increase in interest rates is attributed to a monetary policy shock. A misleading inference from a VAR that suffers from the price puzzle is that surprise monetary policy tightenings cause inflation to rise. One way to "fix" the price puzzle in such VARs is to add commodity prices to the model. Changes in commodity prices can aid in forecasting changes in the price level that are due to supply shocks, although the relationship between commodity prices and the price level is somewhat loose (Boughton and Branson, 1991). This resolution of the price puzzle is similar to my proposed resolution of the monetary policy innovation puzzle: both claim that crucial information is missing from the forecast information set in VARs that exhibit the puzzle.

The purpose of this article is to suggest that the policy innovation paradox described above is an artifact of not taking into account the discreteness of monetary policy changes when forecasting. I show that a simple adjustment to the VAR forecasting procedure makes the policy paradox disappear. That is, a policy innovation is not usually followed by further policy moves in the same direction. Instead, the policy shock immediately begins to decay toward zero. The starting point for my explanation of the policy innovation paradox is that VARs generally use monthly or quarterly averages of the daily effective federal funds rate as a measure of monetary policy actions (Christiano, Eichenbaum, and Evans, 1999, and the references therein). The averaging of daily rates smooths and tends to cancel idiosyncratic fluctuations in daily rates that have nothing to do with monetary policy. In this article, I examine one simple but overlooked aspect of using a monthly or quarterly average of the daily federal funds rate in VARs: Since 1984, the Federal Reserve consistently has adjusted a target level for the federal funds rate by discrete increments. Such discrete adjustments to the target during a month convey information about how the next month's average of daily rates is expected to differ from this month's average.

It is important to consider how knowledge of a discrete target change contributes to forecasting. Consider two hypothetical target changes: in the first, the target is raised by 25 basis points one-third of the way through a month; in the second, the target is raised by 50 basis points two-thirds of the way through a month. In the current month, the monthly average of the daily rates would be the same either way, other things equal. Thus, if one were to forecast the next month's average based solely on current and past values of monthly averages, the forecast for the next month would be identical in both of these cases. Discrete target changes usually persist, however, so knowledge of a target change of 50 versus 25 basis points would affect one's forecast of the average level in the next month. Nevertheless, VARs that include monthly or quarterly averages of the daily effective federal funds rate have ignored information contained in discrete target changes. This article investigates whether including information from discrete target changes in VAR forecasts materially changes inferences about how policymakers proceed after they introduce a monetary policy innovation.

DISCRETE TARGET CHANGES AND FORECASTS OF THE MONTHLY AVERAGE

If a month has N business days and a 50-basis-point (bp) increase in the target federal funds rate occurs N_i business days into the month, then, other things equal, we would raise our forecast of the next monthly average, $\overline{FF}_{t+1}$, by $N_i/N \times 50$ bp above this month's average, $\overline{FF}_t$. If more than one discrete change takes place within a month, then we would alter the forecast by

Table 1

VAR Data Definitions

Inflation	Monthly chain-type price index, personal consumption expenditures (monthly percent change, not annualized)
Unemployment	Percent unemployment in civilian labor force, over age 16
Interest rate	Monthly average of daily effective federal funds rate

(1) $$Z = \sum_i N_i / N \times \Delta FF_{t,i}^T,$$

where the discrete target changes are denoted ΔFF^T. We can include Z_{t-1}, the information imparted by discrete target changes during month $t-1$, as an exogenous regressor that helps forecast the dependent variables in month t. A key hypothesis is that the coefficient on Z_{t-1} in the federal funds rate equation is equal to one. This value would confirm the belief that the expected value of $\overline{FF}_t$ rises one to one with Z_{t-1}, and it would indicate that the forecast errors in the VAR depend significantly on information regarding discrete changes in the target federal funds rate.

A BENCHMARK VAR WITH AND WITHOUT ADJUSTMENT FOR DISCRETENESS

Monthly data since 1984 offer a relatively short sample for a VAR, but this period provides the longest uninterrupted time series on discrete changes to the target federal funds rate (Rudebusch, 1995). The specific sample period is January 1984 to June 2001. To illustrate the puzzle in an uncluttered model, I use Stock and Watson's (2001) benchmark three-variable VAR in levels. They decompose forecast errors into separate orthogonal shocks through a recursive scheme that puts the inflation rate first, followed by the unemployment rate and the average of the daily federal funds rates, with all three of these variables in levels. Specific data definitions are given in Table 1. Twelve lags of all variables are included to purge the residuals of serial correlation at the seasonal frequencies.

As an exogenous variable, we add Z_{t-1} (with no additional lags) to the VAR to include information from discrete target changes. Table 2 reports the coefficients on this discreteness variable. As expected, the coefficient on Z_{t-1} in the federal funds rate equation (1.21) is not significantly different from one (and very significantly different from zero). Here a value of one means that a discrete target change is expected to raise next month's average of daily rates by the full amount of the discrete change. Although the point estimate of 1.21 is not significantly different from one, an estimate above one might make sense in that target changes tend to be positively correlated across time. Thus, forecasters might anticipate that a discrete change in a given month will be followed by an additional discrete change in the same direction in the next month. Table 2 shows that the discreteness variable, Z_{t-1}, is not a significant predictor of either inflation or unemployment, nor is there any reason to expect a direct relationship. In this case, the discreteness adjustment affects only inflation and unemployment through its effect on forecasts of the federal funds rate. Without the exogenous variable, the standard error of the regression in the federal funds rate equation is 0.229, whereas it drops to 0.192 (about 16 percent lower) when the exogenous variable is included. Tables 3 and 4 give more complete results on the coefficient estimates in the VAR.

Table 2

Coefficient on Discreteness Adjustment

Equation	Coefficient value
Inflation	–0.054 (0.102)
Unemployment	–0.167 (0.097)
Federal funds	1.21 (0.141)

NOTE: Standard errors are in parentheses.

One key difference between the two VARs appears in the first two lags of the federal funds rate in the federal funds rate equation. (The other lag coefficients are all small in absolute value and their sum is small, as shown in Tables 3 and 4.) In the model without Z the first two lag coefficients are 1.237 and –0.245; the same coefficients equal 0.924 and 0.026 when Z is included. The presence of Z appears to remove the overshooting and oscillatory

Table 3

Coefficients for VAR without Discreteness Adjustment

Coefficient	Inflation equation	Unemployment equation	Federal funds equation
Inflation$_{t-1}$	0.196 (0.074)	–0.055 (0.072)	0.097 (0.123)
Inflation$_{t-2}$	–0.094 (0.076)	0.112 (0.074)	0.071 (0.126)
$\sum_{i=3}^{12}$ Inflation$_{t-i}$ (sum of lag coefficients)	–0.455	0.163	0.831
Unemployment$_{t-1}$	–0.014 (0.080)	0.746 (0.077)	–0.250 (0.132)
Unemployment$_{t-2}$	–0.112 (0.098)	0.158 (0.094)	–0.112 (0.162)
$\sum_{i=3}^{12}$ Unemployment$_{t-i}$ (sum of lag coefficients)	0.124	0.075	0.309
Federal funds$_{t-1}$	0.160 (0.047)	–0.043 (0.046)	1.24 (0.078)
Federal funds$_{t-2}$	–0.213 (0.075)	0.062 (0.072)	–0.245 (0.124)
$\sum_{i=3}^{12}$ Federal funds$_{t-i}$ (sum of lag coefficients)	0.071	–0.007	–0.041

NOTE: Standard errors are in parentheses.

Table 4

Coefficients for VAR with Discreteness Adjustment

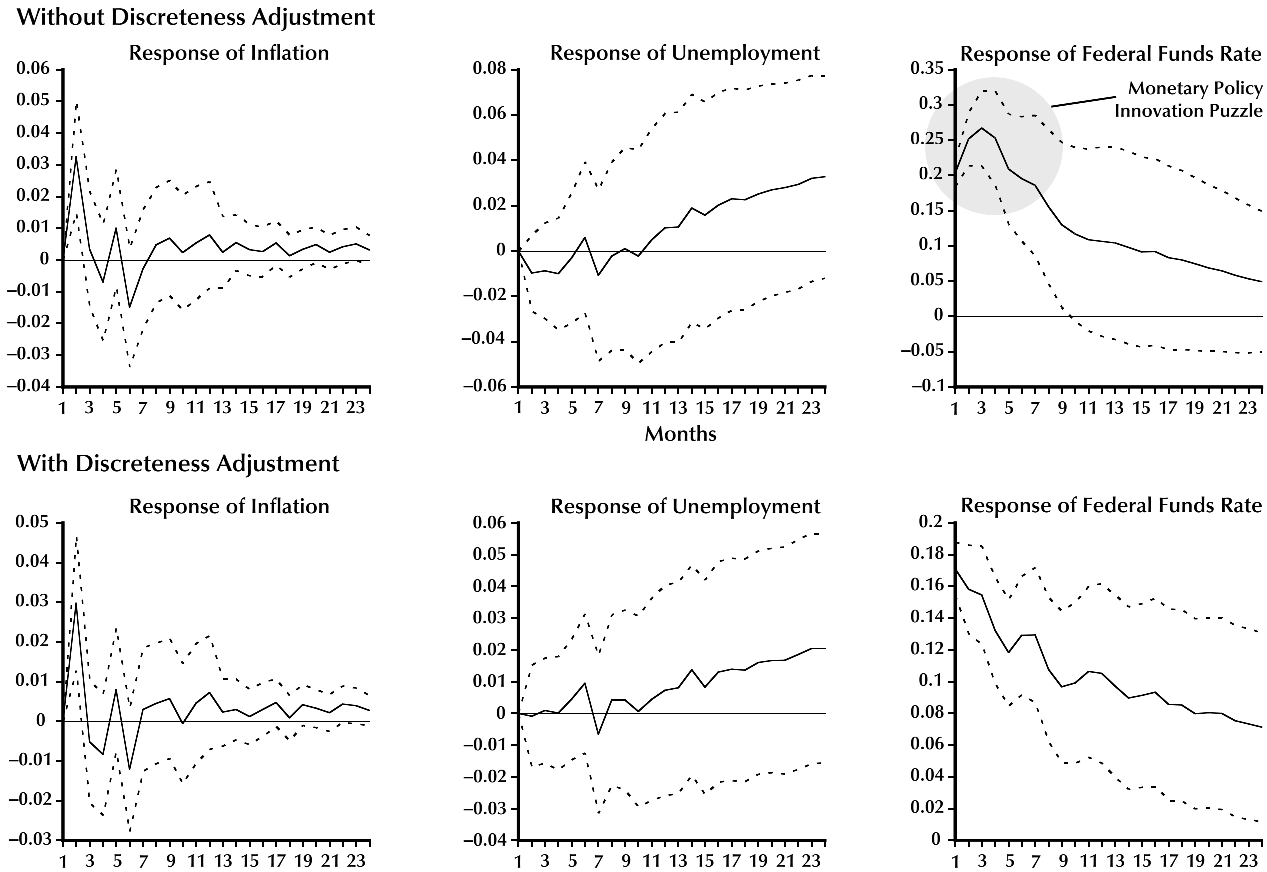
Coefficient	Inflation equation	Unemployment equation	Federal funds equation
Inflation$_{t-1}$	0.194 (0.075)	–0.059 (0.072)	0.124 (0.104)
Inflation$_{t-2}$	–0.090 (0.077)	0.124 (0.074)	–0.014 (0.106)
$\sum_{i=3}^{12}$ Inflation$_{t-i}$ (sum of lag coefficients)	0.473	0.217	0.433
Unemployment$_{t-1}$	–0.016 (0.080)	0.738 (0.077)	–0.188 (0.111)
Unemployment$_{t-2}$	–0.112 (0.098)	0.156 (0.094)	–0.094 (0.136)
$\sum_{i=3}^{12}$ Unemployment$_{t-i}$ (sum of lag coefficients)	0.127	0.084	0.242
Federal funds$_{t-1}$	0.174 (0.054)	–0.006 (0.052)	0.924 (0.075)
Federal funds$_{t-2}$	–0.225 (0.078)	0.024 (0.075)	0.026 (0.109)
$\sum_{i=3}^{12}$ Federal funds$_{t-i}$ (sum of lag coefficients)	0.067	–0.016	0.020
Discreteness adjustment Z_{t-1}	–0.054 (0.102)	–0.167 (0.098)	1.21 (0.141)

NOTE: Standard errors are in parentheses.

dynamics in the federal funds rate that appear in the VAR without Z. In both VAR systems, the largest autoregressive root is over 0.99. The difference is in the oscillatory dynamics, not in the size of the largest root. The overshooting and oscillatory dynamics in the VAR without the discreteness adjustment ought to appear as a hump shape in the impulse response of the federal funds rate to its own shock.

Figure 1

Responses of Inflation, Unemployment, and Federal Funds Rate to a Federal Funds Rate Shock



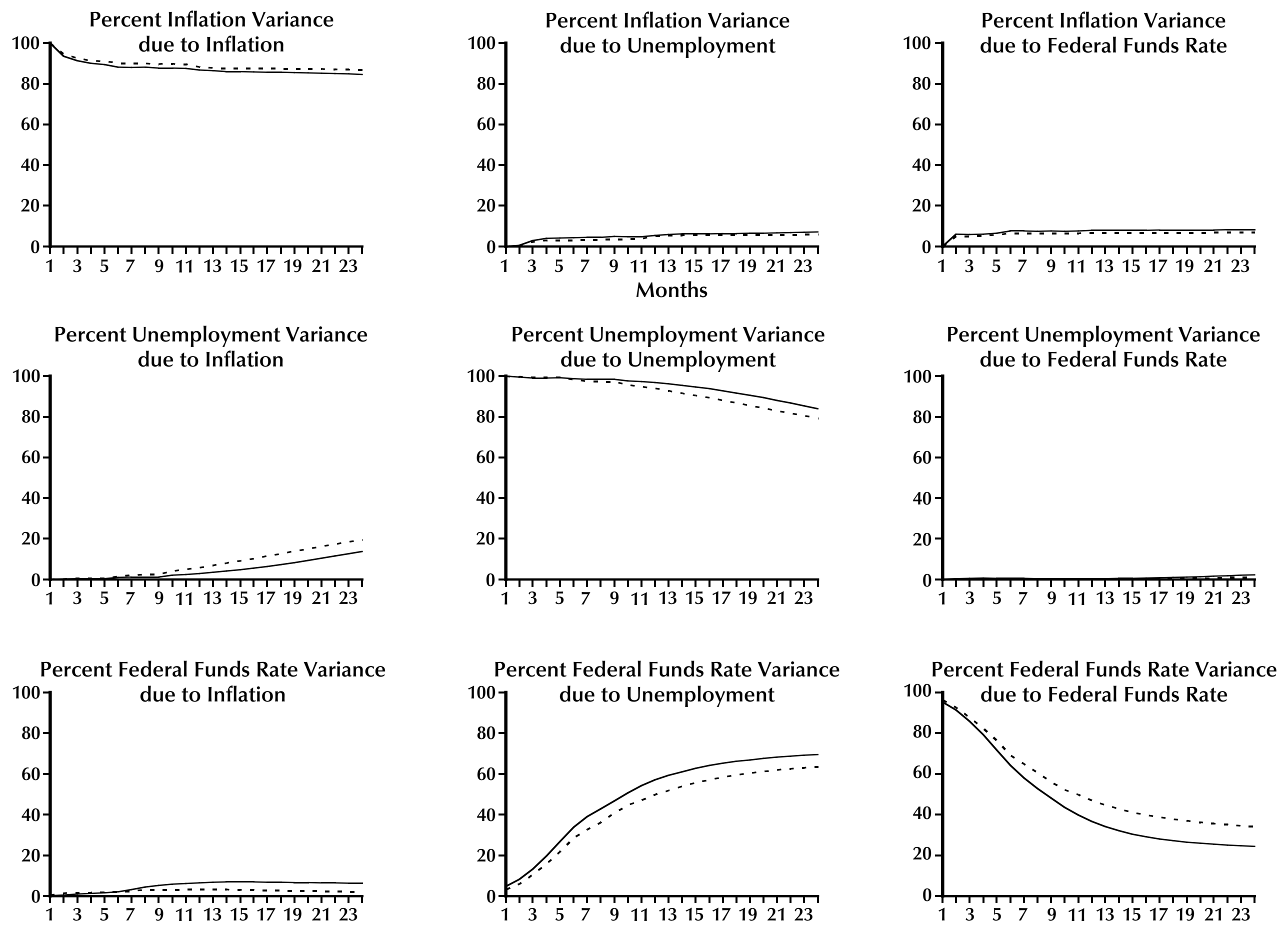
Comparison of Impulse Responses

The impulse response of the federal funds rate to its own shock shows what monetary policymakers tend to do following a surprise increase in the federal funds rate that is not part of a systematic response to an inflation or unemployment shock—i.e., a policy innovation. Without the exogenous variable in the VAR, the impulse response of the federal funds rate to its own shock displays the policy innovation paradox. The upper right panel of Figure 1 shows that, according to this VAR specification, the monetary policy response to a surprise increase in the federal funds rate is to increase it *even more* during the next two months. According to this impulse response, the funds rate remains above the initial shock level until five months after the policy innovation. Such a path for the funds rate would be very difficult to rationalize as a typical monetary policy response. In fact, some VARs identify monetary policy shocks with the assumption that a sensible monetary policy response to a policy innovation or nonsystematic change in the policy instrument is to undo the change relatively quickly (Klaeffling, 2001).

An alternative interpretation of this impulse response, however, is that the continued upward movement of the federal funds rate after the initial shock is an artifact of taking monthly averages of a rate that undergoes discrete shifts within the month. The intuition is that monthly averaging breaks a discrete target change into two pieces: a discrete increase in the target rate in the middle of this month will raise this month's average of daily rates by half of the size of the target change; the other half will appear as an increase in next month's average over this month's average. The key is to forecast the next month's average funds rate in a way that uses information from this month's discrete target change—which is precisely what the exogenous variable Z is designed to do.

Figure 2

Variance Decompositions



NOTE: Dashed and solid lines represent variance decomposition with and without discreteness adjustments, respectively.

The lower right panel of Figure 1 shows the impulse response of the federal funds rate to its own shock when the exogenous variable Z is included in the system. According to this chart, the response of monetary policymakers to a policy innovation or nonsystematic increase in the federal funds rate is to undo it in a gradual, monotonic fashion. As a description of policymaker behavior, this monotonically declining impulse response is much easier to rationalize than a hump-shaped response that rises further before declining.

Figure 1 also shows the impulse responses of inflation and unemployment to monetary policy shocks. As one might expect, these responses do not differ in any significant manner across the two VAR specifications—with or without the discreteness variable Z. We would expect this result given that Z has very low correlations with inflation and unemployment, so that the VAR coefficients are little changed in the presence of Z. Therefore, the discreteness adjustment variable in the VAR has little effect on the cumulative impulse response of inflation and unemployment to a federal funds rate shock. Thus, previous VAR analysis of the effects of monetary policy shocks on the economy is left essentially unchanged with this alteration to the VAR model.

Comparison of Variance Decompositions

While the impulse responses—the response of inflation and unemployment to a given shock—do not differ across the two VAR specifications, the variance decompositions might differ. The discreteness adjustment variable *Z* is designed to help predict the federal funds rate, so its presence might alter inferences regarding the relative frequency of different types of shocks. Figure 2 shows the variance decompositions from the two VAR models. The only notable differences are the variances attributable to inflation shocks. With *Z*, a higher proportion of the variance in unemployment is due to inflation shocks, and a lower proportion of the variance in the federal funds rate is due to inflation. But these differences do not affect qualitative descriptions of which shock accounts for most of the variance in a given variable.

CONCLUSIONS AND SUMMARY

This article considers a straightforward way to make use of information contained in discrete changes to the target federal funds rate when forecasting. The purpose is to show that discreteness is an important feature of the data-generating process for the federal funds rate and that failure to address discreteness affects inferences regarding monetary policymakers' behavior. I apply the approach to a simple three-variable VAR and, not surprisingly, the additional exogenous variable is only a significant predictor of the monthly federal funds rate, not inflation or unemployment. In addition, the discreteness adjustment variable has a coefficient that is not significantly different from one in the federal funds rate equation. We would expect a coefficient of one because the value of this variable is equal to the effect that a discrete target change implies for the change in the daily average from one month to the next, depending on when the change occurs during the month.

This discreteness adjustment nonetheless provides a simple, new explanation for what I call the policy innovation paradox—whereby the reaction of monetary policymakers to their own policy innovation is to push the federal funds rate even farther in the same direction as the initial surprise move. This article shows that the policy innovation paradox disappears once we make use of the discreteness information when forecasting the federal funds rate. Thus, the paradox is simply an artifact of using the monthly average of the daily federal funds rate and failing to take account of the information from discrete target changes when forecasting the monthly funds rate. This resolution of the policy innovation paradox does not affect previous VAR results concerning the effects of monetary policy shocks on other macroeconomic quantities—namely, inflation and unemployment.

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