U.S. Employment Growth and Tech Investment: A New Link

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Abstract

This paper finds a statistically valid link from confidence indexes—CEO, Consumer Confidence and Michigan Sentiment—to investment growth in technology equipment and software, or tech investment, and subsequent job growth in the U.S. employment data for the last 50 years. Our regression analysis allows us to look for factors that can explain the slow pace of job recovery experienced in the last three recessions. Specifically, we identify that tech investment is an important determinant of employment growth, and we identify CEO confidence index as the causal factor for tech investment via the durable goods channel since the late 80's. This result stands even when we substituted the CEO index with either Michigan sentiment or consumer confidence index that are longer time series which capture more expansions and contractions. Thus, a jobless recovery is a facet of a low of confidence level in the economy that affects tech investment, with a good barometer of this investment being orders for durable goods.

Keywords: Employment Growth, CEO Confidence, Technology Investment, Consumer Sentiment, Granger Causality

JEL Classification: C41, D21, E31

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1 Introduction & Motivation

When compared to recoveries from recessions in the United States before the 90's, the 1990-91 and 2001 recoveries were initially jobless and took longer for the economy—approximately three and four years, respectively—to reach the pre-recession peak employment level. The recovery from the 2007-2009 recession seems to be jobless too[1]. This paper uses time-series methods to look for factors that can explain this delay in job recovery after the last three recessions. Specifically, we identify that investment in technology equipment and software (henceforth referred to as tech investment) as an important determinant of employment growth since 1959. Figure 1 illustrates the quarterly U.S. nonfarm employment and tech investment as well as total investment in equipment and software, both in natural logs, from 1959 to 2009. As the graph shows, total investment series leads the cycles of expansion and contraction of the employment series by up to two quarters. For instance, in the recession recorded from 1969Q4 to 1970Q4, investment reached its peak in 1969Q3, while the employment series achieved its maximum in 1969Q4. Additionally, in the recession from 1980Q1 to 1980Q3, investment and employment reached their peaks in 1979Q3 and 1980Q1, respectively. A similar phenomenon also occurs in the recessions of 1981Q3-1982Q4, 1990Q3-1991Q1, and 2001Q1-2001Q4[2]. However, the tech investment series seems to show more comovement with employment in the last three recessions when the recoveries were jobless[3].

We employ a two-step investigative procedure in this paper. We first check for the

[1]The National Bureau of Economic Research (NBER) at the time of this draft had not declared the recession which started in December of 2007 to be over. But a majority of economic forecasters believe that by the real GDP growth, industrial production and retail sales metric the recession ended sometime during the summer of 2009. However, nonfarm employment series, a critical component of dating business cycles, seems to have bottomed out only in December 2009, but the unemployment rate has dropped below its October 2009 peak value of 10.1%. Thus, the challenge in conceptualizing and dating the business cycle in a changing economy is discussed in detail in Sinai (2010).

[2]See NBER website (http://www.nber.org/cycles.html) for reference dates on business cycle expansions and contractions.

[3]Tech investment as a proportion of total investment in equipment and software was less than 20% until mid-80's. It started to rise afterwards and then with the advent of internet and computer usage in mid-90's it rose to be above 50% of the total investment. This break point of mid-80's is also evident in the productivity figures and its implications for Okun's law as analyzed by Gordon (2010).

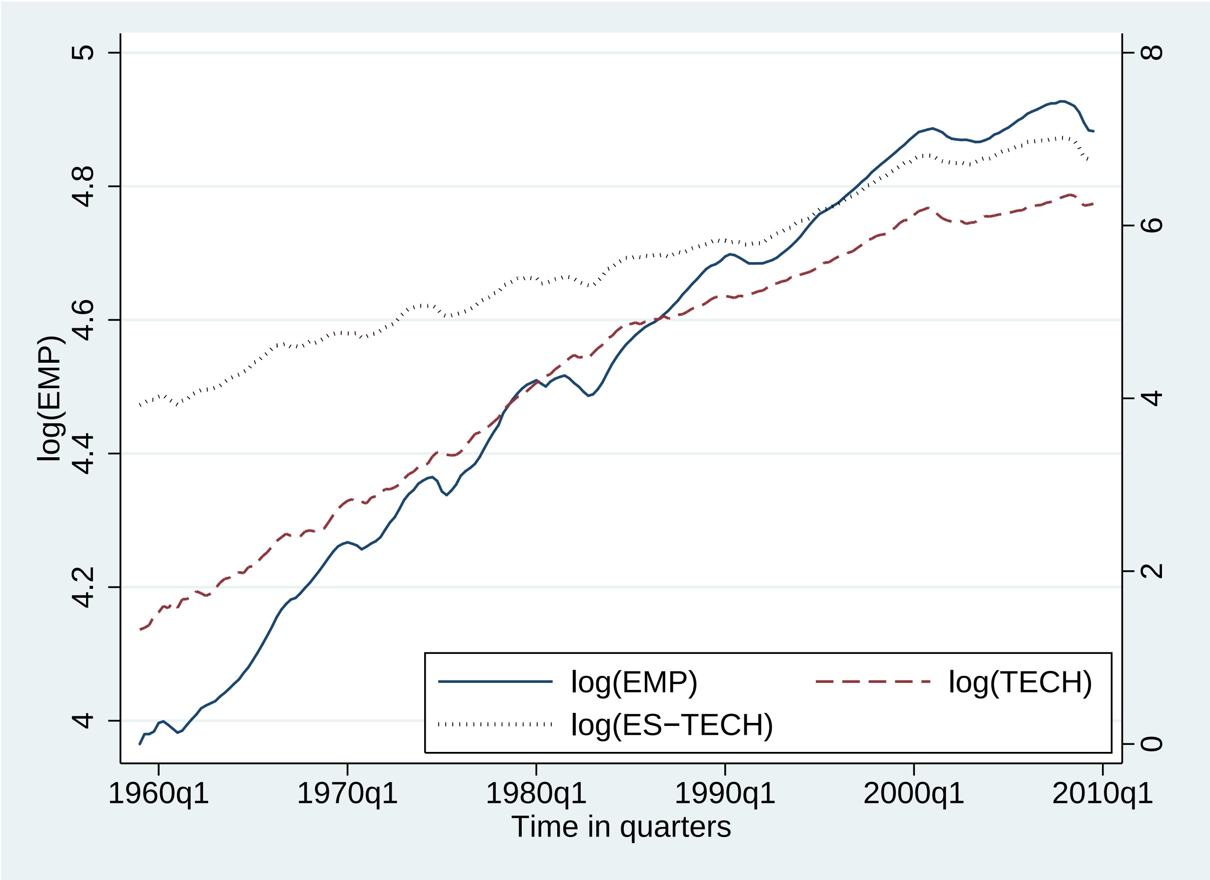

Figure 1: U.S. nonfarm employment and tech investment, 1959Q1 to 2009Q3

direction of causality between tech investment and job growth. Although we did not find them to be cointegrated, we did find that tech investment Granger causes job growth, and vice-versa at one quarter lag, but thereafter up to four lags causality runs only one way from employment to tech investment. As Granger causality tests only check for precedence of one series before the other and not causality as it is usually understood, we ran standard regressions to quantify the impact of investment on employment. Our regression estimates indicate that a 1% permanent jump in the growth rate of tech investment raises the employment growth rate by 0.059%. Thus, a $10 billion increase in tech investment produces an extra 88,000 jobs in the economy. This number rises to 155,000 when we use the bigger measure of investment that includes all types of equipment investment.

Next, we looked for factors that impact tech investment, and identified confidence indexes—Conference Board's CEO confidence and consumer confidence indexes, and University of Michigan's consumer sentiment—as the causal factor for tech investment growth. We found that there seems to be a "double-causality" between CEO confidence and tech investment in the short term (one to two quarter lag), but the CEO confidence "Granger-causes" tech investment at higher lags (three and four quarter lags). The regression estimates show that a 1% increase in the CEO confidence index raises the growth rate of tech investment by almost 0.034%[4]. Thus, a 10 point rise in the CEO confidence index increases tech investment by $4.2 billion. To put more structure to this causal relationship we looked at advance orders for durable goods and found that the CEO confidence index "Granger-causes" durable goods orders up to four quarter lags. The regression results indicate that a 1% increase in the CEO confidence index raises the growth rate of durable goods orders by 0.11%. Thus a 10 point raise in CEO increases manufactured durable goods orders by $8.4 billion.

As the CEO confidence index series only starts in 1988 we also utilized University of Michigan's consumer sentiment series that starts in 1960 and Conference Board's consumer confidence index that starts in 1977Q3. The regression results are very similar when we substituted these series for the CEO index. The Granger test shows a double causality relationship between the Michigan sentiment and tech investment from one up to four lags, at very high significance levels. Also, our regressions show that a one percent permanent increase in the Michigan sentiment index raises the growth rate of tech investment by approximately 0.13%. This rises to 0.16% when we restrict the sample estimation to 1986 onwards. Furthermore for the bigger definition of investment this coefficient is 0.24%. On the other hand, the Granger test identifies only one direction of causality from the consumer confidence to the tech investment series, and we estimated that one percent permanent increase in the confidence index raises the growth rate of tech investment also by approximately 0.137%. Thus, a ten point in either of these indexes raises tech investment by $28.8 billion.

[4]For the bigger measure of investment the CEO confidence raises investment by 0.054%

The paper is organized as following. Section 2 describes the data series used and their sources. Section 3 presents the time series analysis starting with testing for stationarity, undertaking cointegration and Granger causality tests and then performing the regression analysis. Section 4 concludes.

2 The Data

Our analysis relies on quarterly data from the last four decades on nonresidential investment in technology equipment and software (TECH), nonresidential investment in *all* types of equipment and software (ES-TECH), CEO Confidence index (CEO), Michigan consumer sentiment index (MICHIGAN), employment (EMP), and new orders for manufactured durable goods (ORDERS). The economic data and its sources are described as following. TECH, or tech investment, is constructed by adding up the series of investment in computer equipment, software, communications equipment, and other information processing equipment produced by the Bureau of Economic Analysis (BEA). We use quarterly data from 1959Q1 to 2009Q3, measured in billions of 2005 dollars. The ES-TECH series is a broad category of investment that measures the real nonresidential investment in equipment and software. The measure for EMP is total nonfarm payroll, in millions, from 1959Q1 to 2009Q3. This series is obtained from Current Employment Statistics (CES) program of the U.S. Bureau of Labor Statistics Department—details of this survey are in the appendix. We also defined a subcategory of employment called private employment (PRIVEMP) that subtracts government employment from the total number. The private share of employment was approximately 83.5% of the total employment in 2008.

The quarterly CEO confidence index, from the Conference Board, is constructed from a survey of 800 chief executives of corporations in the United States. The index value ranges between 0 and 100 based on their level of optimism, and the data series starts in 1988Q1. The appendix contains the details about the construction methodology of this index. As this series is shorter than the EMP and TECH series, we also utilized Michigan's consumer sentiment survey that starts in 1960Q1 and the Conference Board consumer confidence indexes that starts in 1977Q3—henceforth referred as MICHIGAN and CONFIDENCE, respectively—to substitute for the CEO confidence index as part of our sensitivity analysis[5].

The ORDERS series measures the dollar value of new orders—or intent to buy supported by a strong commitment from the buyer—of manufacturers producing durable goods. The series is obtained at monthly frequency from the U.S. Census Bureau—data construction and survey details are in the appendix, and it is available from 1992Q2. To make the ORDERS series consistent with all our data, we converted this series to quarterly frequency by adding up the months, then we proceed to seasonally adjust the data before doing our statistical analysis[6].

3 Time series analysis

3.1 Unit Root Tests

Table 1 shows the results of the Augmented Dickey-Fuller and the Phillip-Perron tests (henceforth ADF and PP, respectively) on the EMP, PRIVEMP, TECH, ES-TECH, ORDERS, and our three confidence indexes measures: CEO, MICHIGAN, and CONFIDENCE. To test the null hypothesis of unit root, we include the 1%, 5%, and 10% tests' critical values. Panels 1 and 2 present the tests results for the log-levels of the series, $\log(\cdot)$, while panels 3 and 4 show the first difference of the log of the series, $\mathrm{dlog}(\cdot)$. We included a trend and a constant term for the series in log-levels and only a constant term for the series in first differences during the estimations.

[5] The Michigan consumer sentiment index is a monthly survey so we converted it to quarterly frequency by averaging the monthly values in each quarter. This index is positively correlated with the CEO confidence index, however the correlation coefficient changed considerably depending on the years chosen for its calculation. For instance, from 1988Q1 to 2009Q3, the correlation between MICHIGAN and CEO is 0.134. However, the correlation is highly positive at 0.672 from 2001Q1 to 2009Q3. We found similar results when calculating the correlation coefficient between CEO and CONFERENCE. For the whole sample, the correlation between these series is -0.09. However, this correlation increases considerably to 0.389 from 2001Q1 to 2009Q3. Finally, the correlation between MICHIGAN and CONFERENCE is highly positive 0.818.

[6] Durable goods are those with an expected life of at least three years. For the analysis, besides the ORDERS series, we also obtained information on manufacturer's new orders for capital goods. Our results remain consistent when we subtract from both series the component of defense equipment.

The results of the ADF and PP tests suggest that we cannot reject the unit root hypothesis for EMP, PRIVEMP, TECH, ES-TECH, and ORDERS at the standard confidence levels. For the confidence index series, the results of the ADP and PP tests are very different. Both the ADF and the PP tests on the CEO confidence index indicate that we can reject the unit root hypothesis therefore this series is stationary. However, for the MICHIGAN series the ADF test rejects the unit root hypothesis at all conventional significance levels but the PP does not—specifically, the null is not rejected at the 10% critical value, indicating a weak evidence of nonstationarity. Finally, both the ADF and PP tests do not reject the unit root hypothesis for the CONFIDENCE series, hence the CONFIDENCE series is nonstationary[7].

3.2 Cointegration and Causality Tests

We concluded in the previous section that the CEO confidence index is stationary, but the rest of the series—EMP, PRIVEMP, TECH, ES-TECH, ORDERS, MICHIGAN, and CONFIDENCE—are nonstationarity. Now, we proceed to investigate if there is a linear combination among our nonstatinary time series that make them stationary. For this purpose, we use the Johansen's test to evaluate the cointegration hypothesis. This cointegration test is important because it will allow us to rule out a priori any spurious relationships in the series.

Table 2 presents the results of the Johansen's cointegration test for TECH with EMP, PRIVEMP, CONFIDENCE, MICHIGAN, and ORDERS; MICHIGAN with EMP, PRIVEMP, and ORDERS. We also test for cointegration between ORDERS and CONFIDENCE series. The table shows only one cointegration relationship, which relates TECH and CONFIDENCE index series. For the rest of the variables, the Johansen's test rejected the null hypothesis of "at most 1" cointegration equation in favor of no cointegration equations[8].

[7]The difference in the critical values for the tests applied to the CEO, MICHIGAN, and CONFIDENCE series is due to the difference in their sample sizes.

[8]We also ran the Johansen's test subtituting ES-TECH for TECH and the results were almost the

Table 3 shows the Granger causality test on TECH with EMP, CEO, MICHIGAN, and CONFIDENCE series. The first panel identifies only one direction of causality from EMP to TECH, when testing from one up to four lags. Panel 2 shows that causality runs only from CEO to TECH at one and two lags, but then the direction of causality is only from TECH to CEO at higher lags—three and four lags. The third panel of this table shows the Granger causality test between TECH and MICHIGAN confidence index. At one lag, we find that only the MICHIGAN index Granger causes the TECH series. However, from two up to four lags, the test suggest a double causality at high significance levels. The bottom panel shows the Granger test between TECH and CONFIDENCE series. In this case, we cannot reject the null of no causality from TECH to CONFIDENCE, but we do reject this hypothesis from CONFIDENCE to TECH at one and two lags. That is, we found only one direction of causality that runs from CONFIDENCE to TECH up to two lags, then there is no evidence of causality between these series[9].

In table 4, we present the Granger test between the ORDERS series and the three confidence indexes: CEO, MICHIGAN, and CONFIDENCE. Looking at the top panel, at one lag, the test shows that only the CEO confidence index precedes, or "Granger-cause", the ORDERS series at 1% confidence level, but from two up to four lags there is a double causality relationship between ORDERS and CEO. The same results are obtained when using the ORDERS series without the defense equipment component, and the new orders for capital goods, with and without defense equipments as well. The second panel shows no evidence of causality at one lag, in any direction, between ORDERS and MICHIGAN. At two lags, however, the test suggest that ORDERS Granger cause the MICHIGAN index, and vice versa. For three and four lags, the causality only runs from the MICHIGAN

same but the only one cointegration relationship found relates TECH and MICHIGAN index series.

[9]We also run the Granger causality test between ES-TECH and EMP, CEO, MICHIGAN, and CONFIDENCE. We find a double causality between TECH and EMP at one lag. However, when testing from two up to four lags this relationship runs in one direction, from EMP to TECH. When testing causality with the CEO series, we find a double causality between TECH and CEO from one up to three lags, but at four lags the "no causality" hypothesis from CEO to TECH is rejected at 1% significance level. For the MICHIGAN index, from one up to four lags, the test suggests a double-causality between TECH and MICHIGAN at high significance levels. Finally, when testing Granger causality between TECH and CONFIDENCE series, we found only one direction of causality that runs from CONFIDENCE to TECH.

index to the ORDERS series, at 5% significance level—we comment about the causality relationships between alternative measures of durable goods and capital goods orders and the MICHIGAN index in the next footnote. As in the previous case, the bottom panel shows no evidence of causality between ORDERS and CONFIDENCE at one lag, however, we find a double causality relationship between ORDERS and CONFIDENCE from two up to four lags[10].

4 Regression analysis

In this section, we test for the hypothesis that confidence indexes are an important determinant for tech investment, which also significantly explain the employment growth rate in the U.S. economy. Our procedure consists of evaluating the statistical significance and economic magnitude of these relationships in a set of ordinary least square regressions. The results are presented in tables 5 to table 11.

Table 5 shows the regression of the growth rate of employment, dlog(EMP), on the growth rate of tech, dlog(TECH). The adjusted R-square, $\bar{R}^2$, suggest that our model explains between 64% to 68% of the growth rate of total nonfarm employment, and the impact propensity coefficient on tech investment is significant at 1% level, across all specifications[11]. Looking at specifications 3 and 4, the immediate change on the growth rate of employment due to a one unit increase in the growth rate of tech investment is about 0.03%. The coefficient on the first lagged value of tech investment, $t-1$, is not significant but the second lag is strongly negative and significant, at 1% confidence level, and it in-

[10]We find different results in the Granger causality test between the MICHIGAN index and our alternative measures of durable goods and capital goods orders. For instance, when we used the ORDERS series without the capital defense equipment component, we did not find a causality relationship at one lag. However, the Granger test found a double-causality from two up to four lags. For the total new orders for capital goods, there is no causality in any direction at one lag either. However, the causality runs only in one direction from MICHIGAN to the total new orders for capital goods when we tested for two up to four lags. For capital goods orders with no defense equipments, the test shows that causality runs only in one direction at all lags, from the MICHIGAN consumer sentiment index.

[11]We define "impact propensity coefficient" as the coefficient that measures the contemporary change t in the dependent variable, which in this case is the coefficient on dlog(TECH)$_t$. This is different from a "permanent increase" in the dependent variable, which is obtained by adding up the significant coefficients of the chosen specification (see Wooldridge, 2003).

dicates that the change in the growth rate of employment two period after the temporary change on investment is -0.026%, almost offseting the contemporaneous change in TECH. In specification 5, we restricted the sample from 1986Q1 onwards and the magnitude of our estimated coefficients rises significantly, which is explained by the rapid increase of the tech investment series, as a proportion of the total private nonresidential investment, observed in the last two decades. Specification 5 indicates that a permanent increase in TECH raises the growth rate of employment by 0.059%. This estimate increases up to 0.10% when we consider the investment in equipment and software (ES-TECH), a broader category than TECH, as the dependent variable—see specification 6.

We identified the CEO confidence index as the leading factor that might be explaining the growth rate of tech investment from Granger causality testing in the previous section. In table 6 we run a regression of the growth rate of tech investment, dlog(TECH), on the log value of CEO index, log(CEO). The impact propensity coefficient on CEO index is statistically insignificant at all standard confidence levels. However, the lagged CEO variable is significant at 10% and 5% confidence level and it also explains between 27% to 28% of the growth rate of TECH—see specification 3 and 4, respectively. Looking at the regression in column 4 where we use only the lagged CEO variable, we estimated that a one percent increase in the CEO confidence index causes the growth rate of tech investment to rise by 0.034%.

In Table 7 we regress growth rate of ORDERS on the CEO confidence index. Regression in column 2 shows that the impact propensity coefficient of log(CEO) is highly significant, at all standards confidence level and explains about 26% of the growth rate of ORDERS. Regressions in column 3 and 4 show that the coefficients for lagged variables are insignificant. Thus, we ran another regression with only one lagged value of the CEO index, and the coefficient for this variable was highly significant, at 1% confidence level. Thus, a one percentage increase in the CEO index causes approximately a 0.11% change in the growth rate of new orders for manufactured durable goods. Hence, the rise in the CEO index not only explains the changes in the growth rate of tech investment, but also the changes in the growth rate of manufactured durable goods orders—an important determinant for tech investment—which we will demonstrate in the next set of regressions.

In table 8 we identify the channel through which the CEO confidence index affects the tech investment series: the total manufactured durable goods orders, ORDERS. Our regressions show the strong positive and significant relationship, both contemporaneous and lagged, between the durable goods orders and the TECH series. Columns 3 and 4, in this table, show that an immediate change in the growth rate of ORDERS increases the growth rate of TECH by about 0.29%. These estimates are highly significant, at the 5% level, and the regressions explain between 43% to 44% of the growth rate in TECH. The coefficient of the lagged value of ORDERS is also strongly significant at one lag (column 3) but not at two (column 4). According to specification 3, a 1% permanent increase in the growth rate of ORDERS raises the growth rate of TECH by about 0.45%.

The small sample size of the CEO confidence index (from 1988 onwards) only allows us to examine three recession espisodes at the most. To check for the significance and magnitude over a longer time horizon we substituted the CEO index with the MICHIGAN (1960 onwards) and CONFIDENCE (1977 onward) indexes. Tables 9 and 10 show the regressions of the growth rate of TECH on the growth rate of the MICHIGAN and CONFIDENCE series[12].

As we expected, both the MICHIGAN and CONFIDENCE have a strong positive and significant relationship with the TECH series. Table 9 shows that the MICHIGAN confidence index significantly explains the TECH series at one and three lags, for standard confidence levels. However, the explanatory power of these estimations is considerably low. Column 4, with the smallest Akaike criteria, suggests that a one percent permanent increase in the MICHIGAN confidence index raises the growth rate of TECH about 0.13%. Also, this economic magnitude increases to 0.158%, when we include restrict the sample in the tech series from 1986 onwards (column 5). In specification 6, we replace the investment

[12]The strong statistical correlation between the MICHIGAN and CONFIDENCE series (0.91) suggests that these variables could be good substitutes.

in equipment and software series (ES-TECH) for the tech series, and all the estimated coefficients are now significant at the 1% level. The explanatory power of the model also increased substantially from 25% (column 5) to 30% (column 6). This specification suggests that a one percent permanent increase in the growth rate of the MICHIGAN index rises the growth rate of TECH by 0.307%. Table 10 regression results also show that the CONFIDENCE index significantly explains the growth rate of TECH, up to two lags, at 1% and 5% significance levels, and the magnitude of these coefficients is considerable. Column 3 shows that a one percent permanent increase in the CONFIDENCE series raises the growth rate of TECH by about 0.13%, and this estimate is 0.092% when we restrict the sample from 1986 onwards (column 5). Using the broad definition of investment (ES-TECH), the estimate increases to 0.23% (column 6).

We also tested if the MICHIGAN and CONFIDENCE indexes might be good explanatory variables for the growth rate of new order for manufactured goods, and the results are shown in table 11. As we can observe, in column 3, only the second lag of the MICHIGAN series is significant, at a 5% level, but the low $\bar{R}^2$ suggest that there is not a great deal of explanatory power in this regression. On the other hand, the regression in column 6 shows that the growth rate in the CONFIDENCE index significantly affect the growth rate of ORDERS, up to two lags, at all standard significance levels. According to this estimation, a one percent permanent increase in the growth rate of CONFIDENCE causes the growth rate of ORDERS to raise about 0.31%.

5 Conslusion

We have shown that tech investment is an important determinant for job growth in the U.S. economy. Also, our estimations suggest that tech investment increases when the CEO's perceptions about the future of the U.S. economy improve, and the rise in CEO's confidence is reflected in a significant increasing amount of new orders for manufactured durable goods. The estimations are also consistent when we substituted the CEO index for the MICHIGAN and the CONFIDENCE indexes in the sensitivity analysis.

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Table 1: Nonstationarity Tests: Augmented Dickey-Fuller(ADF) & Phillip-Perron (PP)[1]

Variable tested	ADF test	PP test	1% c.v.	5% c.v.	10% c.v.
EMP, PRIVEMP, TECH & ORDERS: in levels[2]					
log(EMP)	2.018	0.088	-4.006	-3.436	-3.136
log(PRIVEMP)	2.128	-0.075			
log(TECH)	1.038	0.538			
log(ES-TECH)	-0.455	-1.838			
log(ORDERS)	-0.487	-1.011	-4.108	-3.481	-3.169
CEO, MICHIGAN & CONFIDENCE: in levels[3]					
log(CEO)	-4.356	-4.253	-4.071	-3.464	-3.158
log(MICHIGAN)	-3.087	-3.190	-4.007	-3.437	-3.137
log(CONFIDENCE)	-2.087	-2.338	-4.031	-3.446	-3.146
EMP, PRIVEMP, TECH & ORDERS: in first differences					
dlog(EMP)	-4.915	-5.230	-3.476	-2.883	-2.573
dlog(PRIV)	-5.220	-5.552			
dlog(TECH)	-10.716	-11.004			
dlog(ES-TECH)	-8.734	-8.965			
dlog(ORDERS)[4]	-5.725	-5.783	-3.555	-2.916	-2.593
CEO, MICHIGAN & CONFIDENCE: in first differences					
dlog(CEO)	-11.122	-11.886	-3.531	-2.902	-2.586
dlog(MICHIGAN)	-15.905	-15.844	-3.478	-2.884	-2.574
dlog(CONFIDENCE)	-10.630	-10.614	-3.501	-2.888	-2.578

[1]The null hypothesis is that the series has a unit root. For the series in log-levels, log, we use a constant and a linear trend assumption. For the series in first differences of the log, dlog, we only employ a constant term in the estimations.

[2]The sample for EMP, PRIVEMP, and TECH series is from 1959Q1 to 2009Q3. The sample for ORDERS series is from 1992Q2 to 2009Q3.

[3]The sample for CEO is 1988Q1-2009Q3, for MICHIGAN 1960Q1-2009Q3, and for CONFIDENCE is 1977Q3-2009Q3.

[4] We also ran the ADF and PP tests for the manufactured durable goods orders without the defense equipment component, as well as for the total new orders for capital goods, including both defense and nondefense components. All results indicate that we cannot reject the unit root hypothesis for these series.

Table 2: Johansen's test for cointegration

Series[1]	**Max. Rank**	**Hypothesis**	**Trace stat.**[2]	**Decision**[3]
EMP & TECH	0	No cointegration	15.0888*	Accepted
	1	Cointegration	7.1184	Rejected
PRIVEMP & TECH	0	No cointegration	20.9344	Rejected
	1	Cointegration	9.8226	Rejected
CONFIDENCE & TECH	0	No cointegration	23.6243	Rejected
	1	Cointegration	5.5551*	Accepted
CONFIDENCE & EMP	0	No cointegration	11.8550*	Accepted
	1	Cointegration	2.3958	Rejected
CONFIDENCE & PRIVEMP	0	No cointegration	11.2076*	Accepted
	1	Cointegration	2.8721	Rejected
MICHIGAN & TECH	0	No cointegration	16.1931*	Accepted
	1	Cointegration	6.7001	Rejected
MICHIGAN & EMP	0	No cointegration	12.5156*	Accepted
	1	Cointegration	2.8839	Rejected
MICHIGAN & PRIVEMP	0	No cointegration	10.9719*	Accepted
	1	Cointegration	2.3442	Rejected
CONFIDENCE & ORDERS	0	No cointegration	14.9131*	Accepted
	1	Cointegration	5.5154	Rejected
MICHIGAN & ORDERS	0	No cointegration	18.1894*	Accepted
	1	Cointegration	7.0558	Rejected
TECH & ORDERS[4]	0	No cointegration	17.7550*	Accepted
	1	Cointegration	4.7999	Rejected

[1]All series are in log-levels. For EMP, PRIV, and TECH the sample is from 1959Q3-2009Q3. For MICHIGAN, CONFIDENCE, and ORDERS the sample start at 1960Q3, 1978Q1, and 1992Q4, respectively.

[2]The " * " indicates the number of cointegrating equations selected.

[3]For "Max. Rank= 0" the 5% and 1% critical values are 15.41 and 20.04, respectively. For "Max. Rank= 1" the 5% and 1% critical values are 3.76 and 6.65, respectively

[4]We also ran the Johansen's test between TECH and the manufactured durable goods and capital goods orders with and without the defense equipment component, and we accepted the null of "No cointegration" in all cases.

Table 3: Pairwise Granger Causality Test: TECH with EMP, CEO, MICHIGAN, and CONFIDENCE

Null Hypothesis[1]	**Lags**	**F-Stat.**	**Prob.**	**Decision**[2]
dlog(TECH) & dlog(EMP); period: 1959Q1-2009Q3				
dlog(TECH) does not cause dlog(EMP)	1	0.53133	0.46691	DNR
dlog(EMP) does not cause dlog(TECH)	1	26.1915	7.3E-07	R. 1%
dlog(TECH) does not cause dlog(EMP)	2	1.80908	0.16654	DNR
dlog(EMP) does not cause dlog(TECH)	2	8.55837	0.00027	R. 1%
dlog(TECH) does not cause dlog(EMP)	3	1.34920	0.25975	DNR
dlog(EMP) does not cause dlog(TECH)	3	8.17923	3.8E-05	R. 1%
dlog(TECH) does not cause dlog(EMP)	4	1.07990	0.36774	DNR
dlog(EMP) does not cause dlog(TECH)	4	7.22601	2.0E-05	R. 1%
dlog(TECH) & log(CEO); period: 1988Q1-2009Q3				
log(CEO) does not cause dlog(TECH)	1	3.69853	0.05789	R. 10%
dlog(TECH) does not cause log(CEO)	1	1.36049	0.24679	DNR
log(CEO) does not cause dlog(TECH)	2	2.60916	0.07985	R. 10%
dlog(TECH) does not cause log(CEO)	2	1.83283	0.16661	DNR
log(CEO) does not cause dlog(TECH)	3	1.94983	0.12859	DNR
dlog(TECH) does not cause log(CEO)	3	2.68754	0.05224	R. 10%
log(CEO) does not cause dlog(TECH)	4	1.40778	0.23977	DNR
dlog(TECH) does not cause log(CEO)	4	2.22305	0.07462	R. 10%
dlog(TECH) & dlog(MICHIGAN); period: 1960Q1-2009Q3				
dlog(MICHIGAN) does not cause dlog(TECH)	1	5.17842	0.02396	R. 5%
dlog(TECH) does not cause dlog(MICHIGAN)	1	1.07883	0.30025	DNR
dlog(MICHIGAN) does not cause dlog(TECH)	2	4.46457	0.01274	R. 5%
dlog(TECH) does not cause dlog(MICHIGAN)	2	3.52748	0.03131	R. 5%
dlog(MICHIGAN) does not cause dlog(TECH)	3	3.11049	0.02759	R. 5%
dlog(TECH) does not cause dlog(MICHIGAN)	3	2.84118	0.03916	R. 5%
dlog(MICHIGAN) does not cause dlog(TECH)	4	2.53485	0.04172	R. 5%
dlog(TECH) does not cause dlog(MICHIGAN)	4	2.84298	0.02551	R. 5%
dlog(TECH) & dlog(CONFIDENCE); period: 1977Q3-2009Q3				
dlog(CONFIDENCE) does not cause dlog(TECH)	1	3.78159	0.05408	R. 5%
dlog(TECH) does not cause dlog(CONFIDENCE)	1	0.06966	0.79228	DNR
dlog(CONFIDENCE) does not cause dlog(TECH)	2	3.30799	0.03993	R. 5%
dlog(TECH) does not cause dlog(CONFIDENCE)	2	0.66597	0.51565	DNR
dlog(CONFIDENCE) does not cause dlog(TECH)	3	1.99632	0.11829	DNR%
dlog(TECH) does not cause dlog(CONFIDENCE)	3	0.76276	0.51715	DNR
dlog(CONFIDENCE) does not cause dlog(TECH)	4	1.59677	0.17990	DNR
dlog(TECH) does not cause dlog(CONFIDENCE)	4	0.63540	0.63826	DNR

[1]Causality is defined in the sense of Granger.

[2] R = reject at 1%, 5%, or 10% confidence level. DNR = do not reject. A rejection means presence of Granger causality.

Table 4: Pairwise Granger Causality Test: ORDERS with CEO, MICHIGAN, and CONFIDENCE. Sample from 1992Q2 to 2009Q3.

Null Hypothesis[1]	**Lags**	**F-Stat.**	**Prob.**	**Decision**[2]
dlog(ORDERS) & log(CEO)				
dlog(ORDERS) does not cause log(CEO)	1	0.46742	0.49661	DNR
log(CEO) does not cause dlog(ORDERS)	1	13.8867	0.00041	R. 1%
dlog(ORDERS) does not cause log(CEO)	2	6.68851	0.00234	R. 1%
log(CEO) does not cause dlog(ORDERS)	2	5.97338	0.00424	R. 1%
dlog(ORDERS) does not cause log(CEO)	3	6.37891	0.00081	R. 1%
log(CEO) does not cause dlog(ORDERS)	3	4.59747	0.00586	R. 1%
dlog(ORDERS) does not cause log(CEO)	4	5.24539	0.00117	R. 1%
log(CEO) does not cause dlog(ORDERS)	4	3.75793	0.00889	R. 1%
dlog(ORDERS) & dlog(MICHIGANIGAN)				
dlog(ORDERS) does not cause dlog(MICHIGAN)	1	0.28136	0.59762	DNR
dlog(MICHIGAN) does not cause dlog(ORDERS)	1	1.56654	0.21520	DNR
dlog(ORDERS) does not cause dlog(MICHIGAN)	2	3.34028	0.04191	R. 5%
dlog(MICHIGAN) does not cause dlog(ORDERS)	2	2.59746	0.08255	R. 10%
dlog(ORDERS) does not cause dlog(MICHIGAN)	3	2.00680	0.12279	DNR
dlog(MICHIGAN) does not cause dlog(ORDERS)	3	3.62009	0.01813	R. 5%
dlog(ORDERS) does not cause dlog(MICHIGAN)	4	1.71626	0.15925	DNR
dlog(MICHIGAN) does not cause dlog(ORDERS)	4	2.9005	0.02980	R. 5%
dlog(ORDERS) & dlog(CONFIDENCE)				
dlog(ORDERS) does not cause dlog(CONFIDENCE)	1	1.63983	0.20490	DNR
dlog(CONFIDENCE) does not cause dlog(ORDERS)	1	2.62880	0.10978	DNR
dlog(ORDERS) does not cause dlog(CONFIDENCE)	2	5.06140	0.00920	R. 1%
dlog(CONFIDENCE) does not cause dlog(ORDERS)	2	3.13019	0.05069	R. 5%
dlog(ORDERS) does not cause dlog(CONFIDENCE)	3	3.89601	0.01315	R. 5%
dlog(CONFIDENCE) does not cause dlog(ORDERS)	3	3.10466	0.03326	R. 5%
dlog(ORDERS) does not cause dlog(CONFIDENCE)	4	3.04707	0.02420	R. 5%
dlog(CONFIDENCE) does not cause dlog(ORDERS)	4	2.96010	0.02738	R. 5%

[1]Causality is defined in the sense of Granger.

[2] R = reject at 1%, 5%, or 10% confidence level. DNR = do not reject. A rejection means presence of Granger causality.

Table 5: Dependent Variable: dlog(EMP)

	(1)	(2)	(3)	(4)	(5)[1]	(6)[2]
dlog(EMP)$_{t-1}$	0.731***	0.723***	0.785***	0.787***	0.766***	0.573***
	(0.046)	(0.050)	(0.049)	(0.050)	(0.064)	(0.059)
dlog(TECH)$_t$	0.026***	0.026***	0.030***	0.029***	0.039***	
	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	
dlog(TECH)$_{t-1}$		0.004	0.004	0.006	0.020*	
		(0.009)	(0.008)	(0.009)	(0.011)	
dlog(TECH)$_{t-2}$			-0.026***	-0.025***	-0.012	
			(0.008)	(0.008)	(0.011)	
dlog(TECH)$_{t-3}$				-0.005		
				(0.008)		
dlog(ES-TECH)$_t$						0.084***
						(0.008)
dlog(ES-TECH)$_{t-1}$						0.016*
						(0.010)
dlog(ES-TECH)$_{t-2}$						-0.013
						(0.009)
Constant	0.001	0.000	0.001**	0.001**	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	201	201	200	199	95	200
Adjusted R-squared	0.64	0.64	0.68	0.68	0.80	0.79
Akaike IC	-1723.40	-1721.59	-1733.97	-1722.65	-906.01	-18.14.77

Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

[1]Sample from 1986Q1 onwards.

[2]Dependent variable is dlog(ES-TECH)$_t$

Table 6: Dependent Variable: dlog(TECH)$_t$

	(1)	(2)	(3)	(4)
dlog(TECH)$_{t-1}$	0.268***	0.505***	0.486***	0.490***
	(0.068)	(0.094)	(0.093)	(0.092)
log(CEO)$_t$		0.017	-0.010	
		(0.017)	(0.022)	
log(CEO)$_{t-1}$			0.041*	0.034**
			(0.022)	(0.016)
Constant	0.018***	0.007***	0.007***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	201	87	86	86
Adjusted R-squared	0.07	0.25	0.27	0.28
Akaike IC	-852.26	-430.33	-426.73	-428.50

Standard errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Dependent Variable: dlog(ORDERS)$_t$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
dlog(ORDERS)$_{t-1}$	0.339***	0.238**	0.175	0.177	0.158
	(0.116)	(0.108)	(0.116)	(0.120)	(0.120)
log(CEO)$_t$		0.109***	0.080**	0.080**	
		(0.028)	(0.035)	(0.035)	
log(CEO)$_{t-1}$			0.052	0.054	0.105***
			(0.038)	(0.042)	(0.031)
log(CEO)$_{t-2}$				-0.003	
				(0.036)	
Constant	0.003	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	68	68	68	68	68
$\bar{R}^2$	0.10	0.26	0.27	0.26	0.25
Akaike IC	-272.21	-284.56	-284.57	-282.58	-281.27

Standard errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Dependent Variable: dlog(TECH)$_t$

	(1)	**(2)**	**(3)**	**(4)**
dlog(TECH)$_{t-1}$	0.268***	0.381***	0.241**	0.239*
	(0.068)	(0.101)	(0.112)	(0.125)
dlog(ORDERS)$_t$		0.284***	0.277***	0.288***
		(0.074)	(0.073)	(0.074)
dlog(ORDERS)$_{t-1}$			0.173**	0.147*
			(0.080)	(0.083)
dlog(ORDERS)$_{t-2}$				0.043
				(0.077)
Constant	0.018***	0.007***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	201	69	68	67
$\bar{R}^2$	0.07	0.39	0.43	0.44
Akaike IC	-852.26	-346.53	-345.66	-388.99

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Dependent Variable: dlog(TECH)$_t$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**^{1}	**(6)**^{2}
dlog(TECH)$_{t-1}$	0.263***	0.268***	0.274***	0.271***	0.360***	
	(0.069)	(0.068)	(0.069)	(0.069)	(0.096)	
dlog(MICHIGAN)$_t$	-0.017	-0.004	-0.003	-0.001	0.044	0.090***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.033)	(0.026)
dlog(MICHIGAN)$_{t-1}$		0.068**	0.069**	0.066**	0.100***	0.082***
		(0.031)	(0.031)	(0.030)	(0.033)	(0.026)
dlog(MICHIGAN)$_{t-2}$			0.035	0.047	0.029	0.072***
			(0.031)	(0.031)	(0.036)	(0.027)
dlog(MICHIGAN)$_{t-3}$				0.064**	0.058*	0.063**
				(0.031)	(0.035)	(0.026)
dlog(ES-TECH)$_{t-1}$						0.388***
						(0.065)
Constant	0.018***	0.017***	0.018***	0.018***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	198	197	196	195	95	195
$\bar{R}^2$	0.06	0.08	0.09	0.11	0.25	0.30
Akaike IC	-842.25	-842.26	-840.52	-841.20	-469.72	-911.79

Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%
[1]Sample from 1986Q1 onwards. [2]Dependent variable is dlog(ES-TECH)$_t$

Table 10: Dependent Variable: dlog(TECH)$_t$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
dlog(TECH)$_{t-1}$	0.437***	0.399***	0.336***	0.310***	0.303***	
	(0.078)	(0.079)	(0.082)	(0.084)	(0.101)	
dlog(CONFIDENCE)$_t$	0.048***	0.046***	0.054***	0.052***	0.043**	0.097***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.015)
dlog(CONFIDENCE)$_{t-1}$		0.031*	0.032*	0.033**	0.049***	0.072***
		(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
dlog(CONFIDENCE)$_{t-2}$			0.044**	0.042**	0.016	0.059***
			(0.018)	(0.018)	(0.020)	(0.017)
dlog(CONFIDENCE)$_{t-3}$				0.007	0.020	0.029
				(0.019)	(0.020)	(0.018)
dlog(ES-TECH)$_{t-1}$						0.196**
						(0.086)
Constant	0.012***	0.012***	0.014***	0.014***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	128	127	126	125	95	125
$\bar{R}^2$	0.24	0.25	0.28	0.27	0.28	0.49
Akaike IC	-604.75	-601.71	-600.15	-599.25	-473.45	-625.01

Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%
[1]Sample from 1986Q1 onwards. [2]Dependent variable is dlog(ES-TECH)$_t$

Table 11: Dependent Variable: dlog(ORDERS)$_t$

	(1)	(2)	(3)	(4)	(5)	(6)
dlog(ORDERS)$_{t-1}$	0.328***	0.297**	0.255**	0.260**	0.153	0.039
	(0.115)	(0.116)	(0.114)	(0.105)	(0.118)	(0.117)
dlog(MICHIGAN)$_t$	0.101	0.104	0.102			
	(0.066)	(0.066)	(0.064)			
dlog(MICHIGAN)$_{t-1}$		0.088	0.100			
		(0.067)	(0.065)			
dlog(MICHIGAN)$_{t-2}$			0.147**			
			(0.066)			
dlog(CONFIDENCE)$_t$				0.126***	0.126***	0.135***
				(0.030)	(0.029)	(0.028)
dlog(CONFIDENCE)$_{t-1}$					0.061*	0.076**
					(0.033)	(0.031)
dlog(CONFIDENCE)$_{t-2}$						0.094***
						(0.030)
Constant	0.004	0.004	0.005	0.004	0.005	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Observations	68	68	68	68	68	68
$\bar{R}^2$	0.12	0.13	0.18	0.28	0.31	0.39
Akaike IC	-272.62	-272.47	-275.63	-286.69	-288.23	-295.91

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%