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Class Struggle and Economic Flactuations: VAR Analysis of the post-War U.S. Economy

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Abstract

Building on Marx's insights in Chapter 25, Volume I of Capital, an augmented version of the cyclical profit squeeze (CPS) theory offers a plausible explanation of macroeconomic fluctuations under capitalism. The pattern of dynamic interactions that emerges from a 3-variable (profit share, unemployment rate and nonresidential fixed investment) vector autoregression estimated with quarterly data for the postwar U.S. economy is consistent with the CPS theory for the regulated (1949Q1–1975Q1) as well as for the neoliberal periods (starting in 1980 or in 1985). Hence, the CPS mechanism seems to be in operation even under neoliberalism.
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Keywords: cyclical profit squeeze, vector autoregression.

1 Introduction

At the aggregate level, capitalist economies are characterized by the twin phenomenon of sustained long-run growth and irregular fluctuations around trend growth. The Marxian tradition of political economy offers powerful and intuitive explanations for both phenomenon. While capital accumulation and (biased) technological change can account for long-run growth, class struggle over the distribution of national income can offer an explanation of the irregular fluctuations that economists refer to as business cycles.

A coherent, classical-Marxist framework to understand long-run economic growth has been developed, drawing on Marx's work, in Foley and Michl (1999); recent empirical work has presented

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evidence in support of this framework (Duménil and Lévy, 2003; Marquetti, 2003; Basu, 2010). On the other hand, Goodwin (1967) presented a formal model of economic fluctuations driven by class struggle between capitalists and workers. Boddy and Crotty (1975) refined this analysis further by linking it explicitly to Marx's analysis in chapter 25 of the first volume of Capital (Marx, 1992), contrasted this classical-Marxian view from a Kaleckian view of "political" business cycles, and presented supporting empirical evidence from the U.S economy for this cyclical profit squeeze (CPS) theory of economic fluctuations.

In a series of important contributions, Jonathan P. Goldstein extended the CPS framework further in two ways. First, Goldstein (1985, 1986) developed a formal model with plausible micro-foundations; second, Goldstein (1996, 1997, 1999) enriched the empirical analysis by using an unobserved components model for estimating key parameters and offering support for the CPS viewpoint.[1]

Several studies have also been critical of the CPS framework (Michl, 1988a,b; Epstein, 1991; Sherman, 1991; Weisskopf, 1992), especially for explaining fluctuations in the neoliberal period, i.e., the period since the mid-1980s. A common point of criticism of the CPS framework relates to the weakening position of labour under neoliberalism. Since the power of labour vis-a-vis capital has diminished in the neoliberal era, the argument goes, profit squeeze explanations of economic fluctuations seem less plausible today. According to this body of critical work, even if the mechanism is at work, it has been substantially weakened. Goldstein (1999) argues for a continued relevance of the CPS mechanism but concedes that it might have weakened since 1985; the empirical results in Tarassow (2010), on the other hand, attempt to show that the mechanism is still in operation in the U.S. economy even after 1985.

This paper revisits the issue of the empirical relevance of the CPS mechanism as an explanation of economic fluctuations under neoliberal capitalism. The basic intuition underlying our empirical analysis is straightforward. Even if there is a secular decline in the power of labour vis-a-vis capital under neoliberalism, which we believe is true, the CPS mechanism might still be in operation. This is because the CPS mechanism, as the name itself implies, is a *cyclical* phenomenon (Mohun and Veneziani, forthcoming). A secular decline (i.e., trend decline) in labour's power is not inconsistent with cyclical fluctuations in the *relative* power of labour vis-a-vis capital. These fluctuations in relative power might very well drive economic fluctuations in a neoliberal environment just as much as it did in a more regulated environment.

Building on Goldstein (1999) and Tarassow (2010), we use a vector autoregression (VAR) methodology to assess the empirical relevance of an augmented CPS model for the U.S. economy. The VAR framework offers a very general framework to analyze co-movements of, and dynamic interactions among, a group of variables with very little *a priori* restrictions (like exogeneity). Since the CPS mechanism involves dynamic interactions among the reserve army of labour, profit share and investment, the VAR methodology is especially suitable for the evaluating the relevance of CPS effects. Our results are *consistent with* the operation of the CPS mechanism, both under regulated and neoliberal capitalism. This suggests that Marx's analysis of the fluctuations of the reserve army of labour, as developed by Boddy and Crotty (1975), remains a powerful analytical

[1] For details of the unobserved components model, also known as the structural time series approach, see Harvey (1989).

framework for understanding macroeconomic fluctuations in capitalism.

Rest of the paper is organized as follows: section 2 discusses the data and highlights some interesting trends; section 3 introduces our empirical model; section 4 discusses our choice of time periods and diagnostic tests on the VAR specification; section 5 presents discussions of the main results; the last section concludes.

2 Data and Trends

To motivate the analysis, Figure 1 presents time series plots of the three macroeconomic variables for the U.S. economy that will appear in an augmented CPS theory of business cycle fluctuations: profit share in the corporate business sector, the civilian unemployment rate and real nonresidential fixed investment. The plots use quarterly data and runs from 1948Q1 to 2011Q1, the whole postwar period.

The first panel in Figure 1 plots the profit share in the U.S. corporate business sector, where the profit share is defined as the ratio of gross operating surplus to the sum of employee compensation and gross operating surplus. Note that this is a measure of the relative share of national income (after removing indirect business taxes) going to capital. The second panel plots the civilian unemployment rate, and the third panel plots an index of nonresidential fixed investment. The 11 recessions, using NBER business cycle dates, are indicated in the figure using shaded vertical regions.[2]

The most striking feature of all the time series plots, especially the income share plot, is the timing of the turning point within each business cycle. For every post-War business cycle, the relative share of income going to capital starts declining *several quarters before the peak*; unemployment declines for a longish period before the peak, and real investment also starts falling just a few quarters before the peak.

The cyclical pattern of profit share movement that underlies the first panel in Figure 1 was highlighted by Boddy and Crotty (1975) as empirical support for the CPS mechanism; it has remained valid in all the business cycles since then, and provides reason to believe that the CPS mechanism might still be in operation.

The cyclical pattern of movements in income share, unemployment and real investment, depicted in Figure 1, could arise because of the CPS mechanism. To understand its logic, let us start at the recovery phase of a typical business cycle. As the recovery picks up, capital accumulation increases, and employment grows; by about mid-expansion, the labour market starts tightening. This signals a change in the power of labour vis-a-vis capital, and is reflected in growing real wages. Competition, both domestic and international, constrains the ability of capitalist firms to raise prices in tandem with growing labour costs. The result is a reversal of the relative shares of income going to capital and labour: from mid-expansion onwards, the share of income going to capital gradually declines.

A recession is necessary to weaken the relative power of labour vis-a-vis capital and halt the decline in the relative income share of capital. This is where investment steps into the story.

[2]Income share data is from NIPA Table 1.14, civilian unemployment rate data is from the FRB St. Louis website, and real nonresidential fixed investment is from NIPA Table 5.3.3.

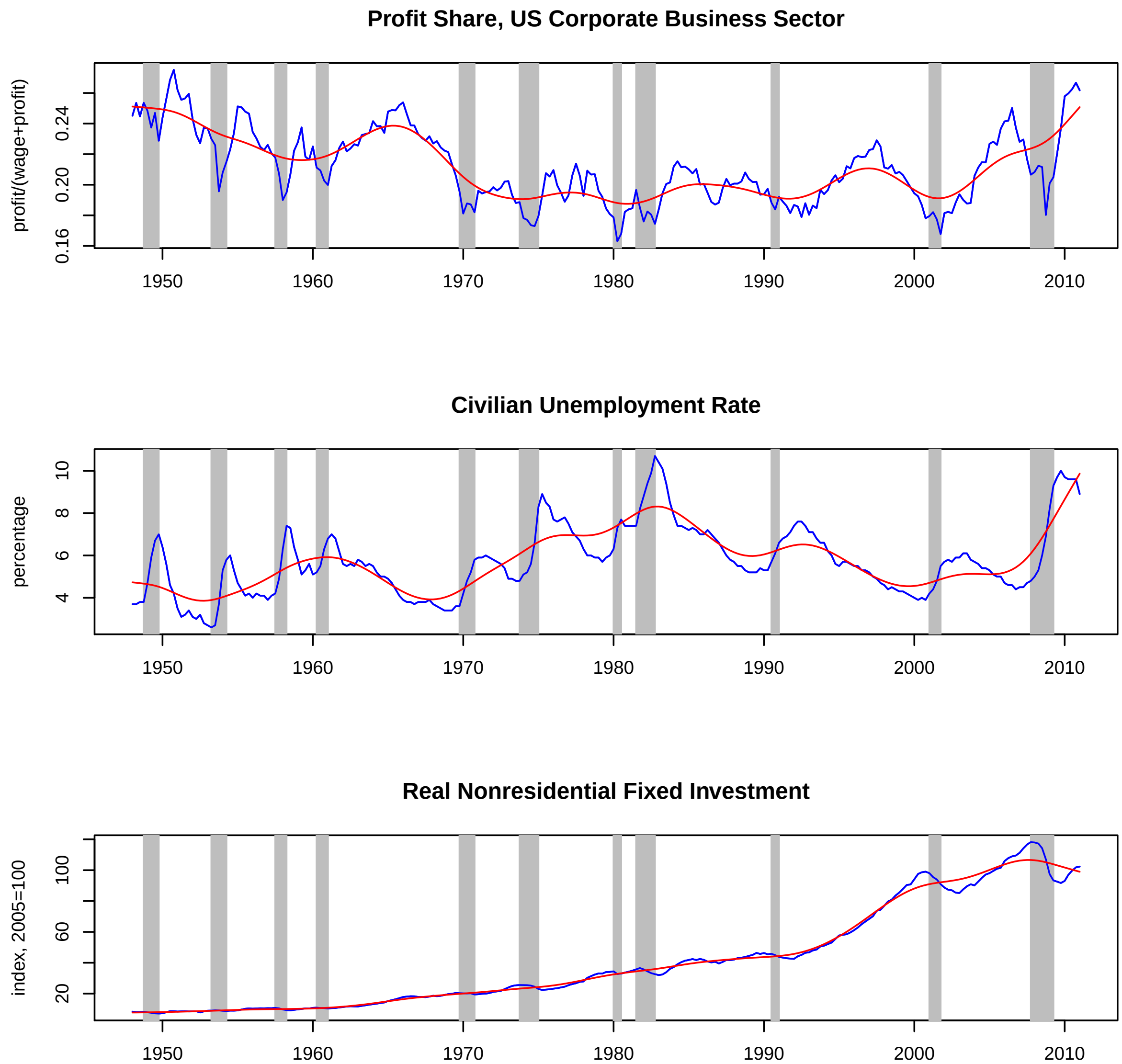

Figure 1: *Time Series Plots (with HP filter trend), for the period 1948Q1–2011Q1, of the three variables that appear in an augmented CPS theory of business cycle fluctuations. The variables are: (1) profit share in the corporate business sector, (2) the civilian unemployment rate, (3) the real (index, 2005=100) nonresidential fixed investment. Time series at a quarterly frequency is used, and vertical shaded regions indicate recessions according to NBER business cycle dates.*

Figure 2: *Time Series Plots, for the period 1948Q1–2011Q1, of the cyclical components in the three variables that appear in an augmented CPS theory of business cycle fluctuations. The variables are: (1) profit share in the corporate business sector, (2) the civilian unemployment rate, (3) the real (index, 2005=100) nonresidential fixed investment. Time series at a quarterly frequency is used, and vertical shaded regions indicate recessions according to NBER business cycle dates.*

There are two channels through which falling profit shares might reduce aggregate investment and reverse the tightening in the labour market. First, since investment responds to current and future profitability, a period of declining profit share eventually puts negative pressures on the incentive to invest. Second, declining profit shares mean declining cash flows; this might, over time, increase the financing constraint on new investment expenditure by capitalist enterprises.

Both these channels imply that close to the peak of the expansion (which, recall, has already been preceded by a few quarters of declining profit share) investment (in real terms) starts declining. With the decline in investment, the demand for labour starts tapering off. The reserve army of labour swells, the labour market loosens and by the end of the recession, i.e., at (or near) the business cycle trough, capital regains its power vis-a-vis labour. The relative share of capital resumes its upward movement, and by mid-expansion, the economy is ready for another cycle.

A note of caution is in order. The time series plots in Figure 1 only indicates, but does not provide any statistical evidence for, the existence of the CPS mechanism. This is because the time series are composed of both trend, possibly stochastic, and irregular cyclical components. Since the CPS mechanism implies relationships between the irregular cyclical components of the variables, a visual inspection of time series plots is not sufficient to assert the existence of the CPS mechanism. To investigate the CPS mechanism, we need to extract the irregular cyclical component from the times series, and then study the relationship between the irregular cyclical components of the three variables.

To make the transition from studying the interaction between the variables to studying the interaction between the cyclical components of the variables, Figure 2 plots the (irregular) cyclical component in each series. The cyclical component is defined as the percentage deviation from the trend, where the trend is estimated by fitting a Hodrick-Prescott filter to the original series.

Figure 2 displays, in a more clear manner, the cyclical movements of the three variables. The same lagged relationship that was highlighted in Figure 1 is also visible in Figure 2. The cyclical component of unemployment, which becomes positive during the recession, starts decreasing during the recovery phase of the cycle. By about mid-expansion, it is close to zero, so that the unemployment rate is back to its trend (and the reserve army is probably back to its long run level). Right around that time, the upward march of the profit share is reversed.

One interesting difference, between the so-called Golden Age (the regulated period of postwar capitalism) and the neoliberal period, is noticeable in the plot of the cyclical component of the unemployment rate. In the recessions of the 1990s, and the early 2000s, the cyclical component of the unemployment rate keeps *increasing* for a few quarters even after the recovery has started. This is in sharp contrast to the scenario in all the previous recessions where the cyclical component of the unemployment rate started falling right after the trough. This change reflects the phenomenon of "jobless recoveries" that has been commented on widely in the literature (for instance, see Basu and Foley, 2011).[3]

Of course, visual inspection of the movements of the cyclical components in the profit share, unemployment rate and real nonresidential fixed investment is not enough to establish the con-

[3]This phenomenon is only observed weakly for the 2007–09 recession because the trend is way too high (due to lack of enough data points *after* the trough). Once more data points become available, the trend will take a more realistic value, and, we believe, the cyclical component of the unemployment rate will display the same delayed response to the "recovery".

tinued relevance, or otherwise, of the CPS mechanism. To carry out a more formal and rigorous statistical analysis of the relationship between the cyclical components, we will complement visual inspection with VAR analysis, a very general empirical framework to study the dynamic interactions among a set of random variables. By summarizing the dynamic interactions among the profit share, unemployment rate and nonresidential fixed investment with impulse response functions, forecast error variance decompositions and Granger causality tests, we will be able to address the question of the continued relevance, or otherwise, of the CPS mechanism.

3 Empirical Model

3.1 Univariate and Vector Autoregression

Let $\tilde{x}_t$ denote the irregular cyclical component of the variable under consideration, i.e., the deviation of a variable x_t from its long term trend; then

$$\tilde{x}_t = x_t - \hat{x}_t,$$

where $\hat{x}_t$ denotes the value of the long term trend of x_t in period t. Note that, in this paper, by the "trend" we do not mean a deterministic time trend; rather, it seems more intuitive to allow for a time-varying, fluctuating trend, which captures the long run evolution of the variable in question. Following a long tradition in macroeconomics, in this paper, we will extract the "trend" of any time series using the Hodrick-Prescott filter with parameter values that are appropriate to the frequency of the data.

A popular way to model time series evolution of stationary macroeconomic variables, which is especially useful for forecasting, has been to use autoregressive (AR) models. For instance, a autoregressive model of order p for the scalar random variable $\tilde{x}_t$ would be specified as

$$\tilde{x}_t = a_0 + b_1\tilde{x}_{t-1} + b_2\tilde{x}_{t-2} + \cdots + b_p\tilde{x}_{t-p} + \eta_t, \tag{1}$$

where $a_0, b_1, \ldots, b_p$ are parameters that are estimated from the data, and η_t is the error term that is uncorrelated across time, i.e., $E(\eta_t\eta_s) = 0$ for $t \neq s$.

It is convenient to interpret (1) in terms of forecasting a scalar random variable using information from the present and past. Within a forecasting framework, (1) asserts that a linear function using p lags of $\tilde{x}_t$

$$f(\tilde{x}_{t-1}, \tilde{x}_{t-2}, \ldots, \tilde{x}_{t-p}) = a_0 + b_1\tilde{x}_{t-1} + b_2\tilde{x}_{t-2} + \cdots + b_p\tilde{x}_{t-p}$$

can be used to forecast current values of $\tilde{x}_t$. Thus,

$$\eta_t = \tilde{x}_t - f(\tilde{x}_{t-1}, \tilde{x}_{t-2}, \ldots, \tilde{x}_{t-p})$$

emerges as the zero-mean forecast error. Hence, if the forecast error is uncorrelated across time, i.e., if $E(\eta_t\eta_s) = 0$ for $t \neq s$, then it implies that p lags contain all the information that is useful for forecasting the current value of $\tilde{x}_t$.

Another way of stating this is to point out that the specification in (1) implies that the movement in $\tilde{x}_t$ is explained by p of its own lags. With the "correct" choice of the lag length, the model asserts that all the important aspects of the current-period value of $\tilde{x}_t$ is contained in its p lags.[4] By ignoring lags $p+1, p+2, \ldots$, the model asserts, we do not lose any essential information about $\tilde{x}_t$. The wide popularity of AR models arise from its being parsimonious, easy to estimate, and useful for forecasting apart from providing a framework that incorporates persistence in time series variables quite naturally.

In macroeconomics, it is natural to think of *many* variables dynamically affecting each other, so that information not only in lags of itself but in lags of other variables might be useful in forecasting a variable; this observation provides the motivation for extending the AR framework to include many as opposed to just one random variable. A vector autoregression (VAR), as an extension of an univariate autoregression, naturally emerges as a way to capture this dynamic interaction among a group of variables.[5]

Collecting k random variables in the k-vector $\tilde{\boldsymbol{Y}}_t$, a vector autoregression of order p, the vector analogue of (1) would be

$$\tilde{\boldsymbol{Y}}_t = \boldsymbol{C}_0 + \boldsymbol{C}_1 \tilde{\boldsymbol{Y}}_{t-1} + \cdots + \boldsymbol{C}_p \tilde{\boldsymbol{Y}}_{t-p} + \boldsymbol{v}_t, \tag{2}$$

where $\tilde{\boldsymbol{Y}}_t, \tilde{\boldsymbol{Y}}_{t-1}, \ldots \tilde{\boldsymbol{Y}}_{t-p}$ in (2) are k-vectors, $\tilde{\boldsymbol{C}}_0, \tilde{\boldsymbol{C}}_1, \ldots, \tilde{\boldsymbol{C}}_p$ are $(k \times k)$ matrices of coefficients, and $\boldsymbol{v}_t$ is a k-vector of white noise errors satisfying $\boldsymbol{E}(\boldsymbol{v}_t) = \boldsymbol{0}$, $\boldsymbol{E}(\boldsymbol{v}_t \boldsymbol{v}_s') = \boldsymbol{0}$ for $s \neq t$, and $\boldsymbol{E}(\boldsymbol{v}_t \boldsymbol{v}_t') = \boldsymbol{\Sigma}_v$, with $\boldsymbol{\Sigma}_v$ a positive definite covariance matrix. If $\boldsymbol{\Sigma}_v$ is a diagonal matrix then the k forecasting errors in $\boldsymbol{v}_t$ are contemporaneously uncorrelated. If, on the other hand, off-diagonal elements in $\boldsymbol{\Sigma}_v$ are non-zero, then the forecasting errors are contemporaneously correlated and this will have important implications in how impulse response functions are identified.

Despite the similarity in form, there is one important difference between (1) and (2) that is worth pointing out. Whereas the univariate model in (1) relates the movement in a variable to its own lags, the VAR model in (2) implies that movements in every variable in $\tilde{\boldsymbol{Y}}_t$ depends on not only its own lags but on the lags of every other variable appearing in $\tilde{\boldsymbol{Y}}_t$. To see this, let us assume that $\tilde{\boldsymbol{Y}}_t$ is a (3×1) vector:

$$\tilde{\boldsymbol{Y}}_t = \begin{bmatrix} \tilde{\pi}_t \\ \tilde{u}_t \\ \tilde{I}_t \end{bmatrix}. \tag{3}$$

Using this in (2) and multiplying out terms, we see that the first row becomes

$$\tilde{\pi}_t = c_1^0 + c_{11}^1 \tilde{\pi}_{t-1} + c_{12}^1 \tilde{u}_{t-1} + c_{13}^1 \tilde{I}_{t-1} + \cdots + c_{11}^p \tilde{\pi}_{t-p} + c_{12}^p \tilde{u}_{t-p} + c_{13}^p \tilde{I}_{t-p} + v_{1t}, \tag{4}$$

where c_{ij}^1 refers to the (i, j) element of the matrix $\boldsymbol{C}_1$ in (2), c_{ij}^2 refers to the (i, j) element of the matrix $\boldsymbol{C}_2$ in (2), and so on. Comparing (1) and (4) we immediately see the difference: while in (1), $\tilde{x}_t$ is explained by its own lags, in (4), $\tilde{\pi}_t$ is explained by its own lags and the lags of $\tilde{u}_t$

[4] This is another way of understanding the meaning of the uncorrelatedness of the forecast error η_t over time.

[5] For an accessible introduction to VAR analysis, see Stock and Watson (2001); for an applied focus see Enders (2011), and for a more technical treatment, see Hamilton (1994), Lütkepohl and Krätzig (2004), or Lütkepohl (2006).

and $\tilde{I}_t$. Moreover, this is precisely what was desired from a forecatsing perspective because in a macroeconomic context it is essential to allow lags of not only itself but lags of other relevant variables to have useful information about a variable.

Each equation in a VAR system will be similar to (4), and this is precisely what is useful for our analysis. By allowing each variable to be impacted not only by its own lags, but also by the lags of all the other variables in the system, the VAR framework allows for the most general way to model the comovements of the group of variables. This easily accommodates complicated patterns of lagged effects among the variables and is precisely what recommends a VAR framework for empirical investigation of the CPS mechanism.

3.2 Empirical Model of Augmented CPS

The traditional CPS mechanism posits a relationship between the $\tilde{\pi}_t$ and $\tilde{u}_t$, where π_t and u_t refer to the share of profit and the unemployment rate, respectively, in period t, and $\tilde{\pi}_t$ and $\tilde{u}_t$, refer to the deviation of each variable from its time-varying long-run trend.[6] Since changes in the profit share impacts on unemployment through investment decisions of capitalist firms, this channel can be made explicit by incorporating nonresidential, I_t, investment as third variable in the model. The 3 variable model, therefore, attempts to capture the relationships between $\tilde{\pi}_t$, $\tilde{u}_t$ and $\tilde{I}_t$; following Goldstein (1999), we will refer to this as the *augmented* model of the CPS mechanism.

Collecting the three variables - the deviations of the profit share, unemployment rate and non-residential fixed investment from their respective trends - in the (3×1) vector $\tilde{\boldsymbol{Y}}_t$,

$$\tilde{\boldsymbol{Y}}_t = \begin{bmatrix} \tilde{\pi}_t \\ \tilde{I}_t \\ \tilde{u}_t \end{bmatrix}, \tag{5}$$

the empirical model of the augmented CPS mechanism becomes

$$\tilde{\boldsymbol{Y}}_t = \boldsymbol{B}_0 + \boldsymbol{B}_1\tilde{\boldsymbol{Y}}_{t-1} + \cdots + \boldsymbol{B}_p\tilde{\boldsymbol{Y}}_{t-p} + \boldsymbol{\varepsilon}_t. \tag{6}$$

where $\tilde{\boldsymbol{Y}}_t$ is the (3×1) vector appearing in (5), and $\boldsymbol{B}_0, \boldsymbol{B}_1, \ldots \boldsymbol{B}_p$ are (3×1) coefficient matrices, and $\boldsymbol{\varepsilon}_t$ is the (3×1) vector of errors with $\boldsymbol{E}(\boldsymbol{\varepsilon}_t) = \boldsymbol{0}$, $\boldsymbol{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_s') = \boldsymbol{0}$ for $s \neq t$, and $\boldsymbol{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \boldsymbol{\Sigma}_{\varepsilon}$, with $\boldsymbol{\Sigma}_{\varepsilon}$ a postive definite covariance matrix.

The model in (6) is similar to the models used in the early work on VARs by, for instance, Sims (1980); Fischer (1981); Koray and Lastrapes (1989). The model implies that there are no direct contemporaneous relationships among the three variables appearing in the augmented CPS mechanism. The contemporaneous relationships are captured by those arising among the forecasting errors.

[6]The unemployment rate is a measure of labour market tightness, itself a proxy for the relative power of labour vis-a-vis capital. Other measures that could be used are: employment-population ratio, median (or mean) duration of unemployment.

3.3 No Contemporaneous Effects

The fact that there are no contemporaneous relationships between the three variables in the VAR is crucial for the analysis in this paper; hence it deserves some discussion. We motivate the lack of contemporaneous relationships between the cyclical fluctuations of the profit share, unemployment rate and real nonresidential investment by drawing on the existing heterodox literature that has studied these relationships.

First, Boddy and Crotty (1975), and later Goldstein (1985, 1986), had emphasized that the effect of declining unemployment rate on the profit share operates only with a lag; that is precisely what is depicted in Figure 1. Only after unemployment has fallen for a while does it lead to sufficient tightness in the labour market that can alter the relative power of labour vis-a-vis capital; that is why the share of profits starts falling only from the mid-expansion and not from the beginning of the expansion. There is no a priori reason why cyclical fluctuations in investment have a contemporaneous impact on profit share; we think, it is likely to have a lagged impact only because of significant time lags between investment, production and sales. Hence, we think it is justified to rule out any contemporaneous impact of unemployment and investment on the profit share.

Second, the fact that investment decisions involve lags have been emphasized by Skott (forthcoming). Changes in cyclical component of unemployment as indicators of aggregate demand conditions, and changes in profit share as indicators of the ease of financing conditions operate on capitalist firms' investment decisions only with a time lag. Hence, we can rule out contemporaneous effect of unemployment rate and profit share on cyclical fluctuations of investment.

Third, we think that profit share has an indirect effect on the unemployment rate which operates through investment decisions (capital accumulation) of capitalist enterprises. Changes in the cyclical component of profit share, as we have just now argued, will plausibly only have a lagged impact on investment. On the other hand, changes in the cyclical fluctuations of investment is likely to have only a lagged impact on the unemployment rate due to labour saving technical change, global relocation of production, labour hoarding and other such mechanisms in operation in the capitalist labour market. This implies that there will be no contemporaneous impacts of the profit share and investment on the cyclical fluctuations of the unemployment rate.

4 Time Periods and Diagnostics

4.1 Time Periods

In this section, we report OLS estimation results of the VAR model using U.S. data at a quarterly frequency; we carry out the analysis for three different time periods: 1949Q4–1975Q1, 1980Q3–2011Q1 and 1985Q1–2011Q1. The first period covers the so-called Golden Age of capitalism, starting with the trough of the first post-War recession and ending with the trough of the recession in 1975 that drew the age of regulated capitalism to a close. The second period covers the neoliberal period of U.S. capitalism, and runs from the trough of the 1980s recession to the trough of the recession that heralded the structural crisis of neoliberalism.

The third period also covers neoliberal capitalism, but starts in 1985. This starting point is dictated by two considerations. First, it seems reasonable to assume that the neoliberal framework would take a few years to consolidate itself; hence its effects would show only a few years after the recession that announced its existence in 1980. Second, Goldstein (1997, 1999) identified the year 1985 with a structural break; hence, it offers itself as a good starting point. Both these considerations suggest that we use a time period running from 1985; hence, we chose the third period.

Recall, from (5), that the variables in the VAR are: (1) deviation of profit share of the corporate business sector from its HP filter trend, $\tilde{\pi}_t$; (2) deviation of real nonresidential fixed investment from its HP filter trend, $\tilde{I}_t$; and (3) deviation of civilian unemployment rate from its HP filter trend, $\tilde{u}_t$. Hence, the specification of the VAR model we estimate is

$$\tilde{\boldsymbol{Y}}_t = \boldsymbol{B}_0 + \boldsymbol{B}_1 \tilde{\boldsymbol{Y}}_{t-1} + \cdots + \boldsymbol{B}_p \tilde{\boldsymbol{Y}}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{7}$$

where $\tilde{\boldsymbol{Y}}_t$ is a (3×1) vector of the cyclical fluctuations of profit share, unemployment rate and real nonresidential fixed investment. We estimate the model with 8 lags, in effect allowing a period of 2 years for dynamic effects to work themselves out.

An alternative specification of the VAR model would include, following Goldstein (1999), two dummy variables, one for the early expansion and the other for the recession, to capture the effects of the stage of the business cycle on the variables in the VAR,

$$\tilde{\boldsymbol{Y}}_t = \boldsymbol{B}_0 + \boldsymbol{B}_1 \tilde{\boldsymbol{Y}}_{t-1} + \cdots + \boldsymbol{B}_p \tilde{\boldsymbol{Y}}_{t-p} + \boldsymbol{D}\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t, \tag{8}$$

where $\boldsymbol{X}_t$ is a (2×1) vector of exogenous dummy variables,

$$\boldsymbol{X}_t = \begin{bmatrix} EEXP_t \\ REC_t \end{bmatrix},$$

with $EEXP$ being a dummy for early expansion, and REC a dummy for recession, and $\boldsymbol{D}$ a (3×2) matrix of coefficients which capture the impact of the stage of the business cycle on the three variables in the CPS mechanism.[7]

We estimated this alternative specification with phase-of-business-cycle dummies, but do not discuss it any detail here, for two reasons. First, while its true that the relationships among the three variables in the VAR change over the phases of the business cycle, including dummy variables for the phases of the business cycle does not capture this phenomenon. To capture the changing relationship over the phases of the business cycle would require interacting the dummy variables with the three main variables in the VAR, a procedure that is ruled out in the VAR framework. Second, the VAR framework, by allowing for lagged effects, already captures the changing relationships among the three variables over the different phases of the business cycle. Hence, inclusion of the dummies seem unnecessary, and our preferred specification excludes the dummy variables.

4.2 Diagnostics

Table 1 and Figure 3 presents statistics from diagnostic tests of the VAR model in (7). The main specification test that is crucial to the validity of the results is the test of autocorrelation in the VAR errors.

[7] We could follow Boddy and Crotty (1975) to construct the dummy variables for the stage of the business cycle.

Table 1: *Diagnostic Tests*[a]

	1949Q4–1975Q1	1980Q3–2011Q1	1985Q1–2011Q1
Serial Correlation	0.211	0.342	0.497
Normality	0.200	0.000	0.000
Skewness	0.180	0.011	0.016
Kurtosis	0.299	0.001	0.005

[a] This table reports diagnostic test results for estimation of the VAR in (6) with 8 lags. For both the serial correlation and normality tests, p-values are reported in this table. The null hypothesis for the serial correlation test is that the VAR errors do not have serial correlation until lag 16. A large p-value implies that the null hypothesis cannot be rejected. The Jarque-Bera normality test is a test of jointly normal VAR errors.

For a VAR model, autocorrelation means that the errors of each regression are correlated over time. In a static setting autocorrelation in regression errors reduce the efficiency, although the OLS coefficient estimates remain unbiased. In a VAR setting, which is inherently dynamic, presence of autocorrelated errors can make the OLS estimates inconsistent and invalidate statistical inference using t and F tests.

We use a standard Portmanteau test to examine whether there is any evidence of autocorrelation in the VAR residuals. In our case, we are testing whether any such autocorrelation relationship exists when we allow for as many as 16 lags. Since what we have is a relatively large sample, we can just use the original form of the test, instead of using its adjusted form for testing small samples. The result in the first row of Table 1 (with all relatively large p-values) suggests that we cannot reject the null hypothesis that there is no autocorrelation existing at least until 16 lags. This allows us to comfortably rule out strong autocorrelation in the VAR errors.

The next diagnostic test we carried out is a test of the normality of the VAR errors. A violation of the normality assumption (i.e. error distribution is non-normal) could also distort the estimation of coefficients and calculation of confidence intervals. For this issue, we apply Jarque-Bera normality tests to the residuals of the VAR model to see whether the multivariate skewness and kurtosis match a normal distribution. The joint null hypothesis is that skewness is zero and that excess kurtosis is also zero. The testing results reject the null hypothesis, showing that the joint distribution of errors is non-normal other than in the regulated period, 1949Q4–1975Q1. While this raises some concerns, we can be reasonably certain about the validity of our results because we have a large sample. Since we have relatively large samples, reliance on asymptotic arguments allows us to circumvent the problems that arise due to non-normal errors.

The third diagnostic test that we report is a test of parameter stability. The CUSUM test help us detect any structural change with unknown change point. The result (in Figure 3) suggests that within each of the three time periods, there is no significant structural change happening. Since the estimates lie within the error band, this suggests that the parameter estimates are stable.

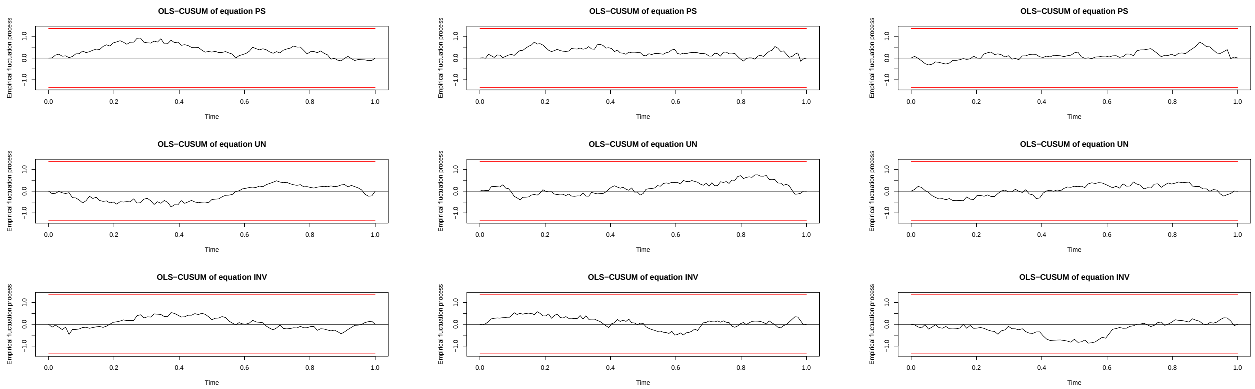

Figure 3: *Testing for parameter stability. The figures plot the parameter estimates along with 95 percent confidence intervals from a CUSUM test. The first column is for the period 1949Q4–1975Q1, the second for the period 1980Q3–2011Q1, and the third is for the period 1985Q1–2011Q1.*

5 Results

5.1 Contemporaneous Residual Correlations

We start discussing our results by looking closely at the correlation matrices of the VAR residuals reported in Table 2. The fact that the contemporaneous correlations are relatively large, i.e., larger than zero, suggests that our assumption about contemporaneous effects working through the relationships of the innovations are justified.

The signs of the correlations are all along expected lines. Thus, the forecast error of profit share and investment are positively correlated, suggesting that unexpected changes in profit share and investment move in the same direction. This might be interpreted as suggesting that unexpected increases in profit shares are positively correlated with investment, either through the expectational channel or through the finance channel.

The forecast errors of unemployment and profit share are negatively correlated, implying that unexpected changes in unemployment and profit shares move in opposite directions. This makes intuitive sense: sudden increases in profit shares might increase investment and thereby reduce the unemployment rate. Similarly, the forecast error of unemployment and investment is negatively correlated, with an analogous interpretation.

Looking at the magnitudes of the correlations we notice an interesting pattern. While the magnitude of the correlation between unemployment innovation and investment innovation has more or less remained constant around a value of 0.5, the magnitude of the correlations between the profit share innovation and the investment (and unemployment) innovation has significantly declined. This suggests a weakening of the link between positive innovation to profit shares and investment, thereby also reducing the link between positive profit share innovations and the unemployment rate.

Table 2: *Contemporaneous Correlation Matrices of VAR Residuals*[a]

	1949Q3–1975Q1			1980Q3–2011Q1			1985Q1–2011Q1		
	PS	INV	UN	PS	INV	UN	PS	INV	UN
PS	1.00			1.00			1.00		
INV	0.50	1.00		0.09	1.00		0.11	1.00	
UN	-0.45	-0.54	1.00	-0.19	-0.46	1.00	-0.21	-0.51	1.00

[a] Contemporaneous correlation among the residuals in the VAR model in (6) estimated with 8 lags. PS: deviation of profit share from trend; INV: deviation of real nonresidential fixed investment from trend; UN: deviation of civilian unemployment rate from trend.

5.2 Coefficient Estimates

In this section we discuss the coefficient estimates. When there are many lags in the VAR, as is the case in this paper, using the IRF to analyze dynamic interaction among the variables is more informative than reporting the estimates of all the coefficients. Hence, in Table 3 we report the coefficient estimates only for two lags of each variable.

The main pattern that emerges from the results in Table 3 is that all the three variables in the VAR -deviation of profit share from trend, deviation of real nonresidential fixed investment from trend, and deviation of civilian unemployment rate from trend- are positively impacted by their first lags. This pattern is consistently observed for all the three periods of analysis.

Profit share is not impacted (in the sense of statistical significance of the coefficient estimates) by the first two lags of the other two variables, but investment is impacted negatively by the first lag of unemployment and unemployment is impacted negatively by the first lag of the profit share.

It is difficult to put much emphasis on these results because there are many more lags that we have left out and often variables are significantly at longer than two lags. Since we are interested in understanding the *dynamic* interactions among the three variables in the VAR without imposing any a priori restrictions, it is better to study impulse response functions, forecast error variance decompositions and Granger causality tests than attach much importance to the coefficient estimates.

5.3 Orthogonalized Impulse Response Function

Dynamic interactions among the variables in the VAR can be studied using impulse response functions (IRF), which trace the time path of each variable to a one-unit one-time increase (i.e., impulse) to the relevant VAR error. The IRF is useful for our purposes because it allows us to directly assess the presence of cyclical interactions among the variables in the VAR system: if the time path of any variable does not die out immediately but instead oscillates between negative and positive values, then this provides evidence of cyclical movement for that variable.

We orthogonalize the innovations using the Choleski decomposition method of Sims (1980). This means that the IRF depends on the "order" of the variables in the VAR. Hence, we report IRFs for three different orderings of the variables in the VAR. Since we get the same basic result, viz.,

Table 3: *Coefficient Estimates from the VAR*[a]

	1949Q3–1975Q1			1980Q3–2011Q1			1985Q1–2011Q1		
	PS	INV	UN	PS	INV	UN	PS	INV	UN
PS, 1 LAG	0.62***	0.22	-0.75*	0.58***	0.11*	-0.19	0.59***	0.09	-0.25*
PS, 2 LAG	0.07	-0.01	0.57	0.04	-0.05	0.08	0.00	-0.06	0.05
INV, 1 LAG	-0.03	0.66***	0.26	-0.26	1.00***	-0.29	-0.46	0.95***	-0.43
INV, 2 LAG	-0.23	0.12	-0.25	-0.09	-0.04	0.14	0.06	-0.04	0.14
UN, 1 LAG	0.09	-0.11*	1.18***	-0.20	-0.13	1.13***	-0.28	-0.16*	1.03***
UN, 2 LAG	-0.03	0.17*	-0.36	0.08	0.06	-0.18	0.17	0.05	-0.13

[a] Coefficient estimates from the VAR model in (6) estimated with 8 lags. PS: deviation of profit share from trend; INV: deviation of real nonresidential fixed investment from trend; UN: deviation of civilian unemployment rate from trend. Columns stand for dependent variables, and rows for the left hand side variables. We only report estimates for 2 lags.

fluctuations in the time paths of the three variables in the VAR to impulses from each error, we are confident that our results are not the artifact of any particular ordering.

Figure 4 presents orthogonalized impulse response function (IRF) plots for the following order: PS → INV → UN. This particular ordering means that the error in the unemployment equation has no contemporaneous effect on the errors in the profit share and investment equations; the error in the investment equation impacts the error in the unemployment equation, but not profit share equation, contemporaneously; and, the error in the profit share equation can contemporaneously impact the errors in both the investment and unemployment equations.

Figure 5 presents orthogonalized impulse response function (IRF) plots with the following order of the VAR variables: INV → UN → PS. Figure 6, on the other hand, presents orthogonalized impulse response function (IRF) plots for the following ordering of the variables in the VAR: UN → PS → INV. Both these IRFs have interpretations about the errors that are analogous to the interpretation of the errors in the IRF in Figure 4. There are at least three noteworthy features of the IRFs.

First, for all the three orderings of variables in the VAR, the IRF plots display significant fluctuations around the zero line. Hence, irrespective of the ordering of the variables, shocks to each error traces out oscillations in the time paths of each of the three variables. While the contemporaneous effects differ by the orderings of the variables, the overall pattern of fluctuations remain the same. Hence, the dynamic patterns of interaction among the three variables are consistent with the CPS mechanism no matter which way we choose to orthogonalize the innovations.

Second, the unemployment rate series shows consistently stronger fluctuations to the impulses in the errors of the profit share and investment equations. Moreover, this pattern is observed in all the three orderings. This seems to suggest that the impact of shocks to demand (investment) and distribution (profit share) translate into large fluctuations in the reserve army of labour. Shocks to the the reserve army of labour, on the other hand, do not seem to have similarly sized impacts on demand and income distribution.

Third, while the fluctuations in unemployment are roughly of equal magnitude in the neoliberal and in the regulated period of postwar capitalism, fluctuations in profit share and investment seem larger in magnitude in the neoliberal period. Moreover, the exact starting point of the neoliberal period does not change the pattern of the IRF; both for the 1980Q3–2011Q1 and 1985Q1–2011Q1 periods, we observe similar fluctuations in the response path of the three variables in the VAR.

5.4 FEVD and Granger Causality

Recall that there are three ways to summarize information about the dynamic interactions among the variables in a VAR: impulse response functions, forecast error variance decompositions (FEVD) and Granger causality tests. Having discussed IRF in some detail, we now present results on FEVD and Granger causality tests for a VAR with the following ordering: PS → INV → UN.

Table 5, 6, and 7 give results of the forecast error variance decomposition for a 10-quarter forecast horizon for the periods 1949Q4–1980Q3, 1980Q3–2011Q1, and 1985Q1–2011Q1 respectively. The forecast error variance decomposition (FEVD) tells us the proportion of the movements in a variable due to its own shocks versus shocks to other variables in the VAR. In other words, it measures the relative weight of each structural shock for the explanation of the total variance of each variable. Table 5, 6, and 7 suggests that, as the forecast horizon approaches 10 lags, considerable portions of the variation of each variable can be explained by shocks from other variables. This suggests significant interaction among the three variables in the VAR, especially lagged interactions.

Table 4 presents results from Granger causality tests. A test of Granger causality is not a test causality in the standard sense of the word; it is a test of improvement in forecasting. When a variable in a VAR is said to Granger cause another variable in the same VAR system, this means that lags of the first variable helps in improving forecasts of the second variable. When a variable has no information that might help in improving the forecast of another variable in the VAR of which both are parts, then the first variable is said to have failed to Granger cause the second.

In VAR systems with stationary variables, Granger causality can be implemented as F-tests of the joint null hypothesis that all lags of a particular variable has zero coefficients. If this null hypothesis is rejected then this variable can be said to Granger cause the dependent variable in the relevant equation of the VAR.

Table 4 shows that investment does not Granger cause profit share for all the three periods. On the other hand, unemployment Granger causes profit share in the regulated period but does not Granger cause profit share in the neoliberal period. This suggests a weakening of the link running from unemployment (the reserve army of labour) to profit share (income distribution) in the neoliberal period.

Turning to investment we see from Table 4 that the profit share does not Granger cause investment for all the three periods. On the other hand, unemployment seems to weakly Granger cause investment in the regulated period but does not Granger cause investment in the neoliberal period.

What do we see with respect to the Granger causality of unemployment? Table 4 shows that profit share Granger causes unemployment in all the three periods, the effect being stronger in the regulated period. Investment has the opposite effect: it does not Granger cause unemployment in the regulated period but strongly Granger causes unemployment in the neoliberal period.

Table 4: *Granger Causality Test*[a]

	1949Q4–1975Q1			1980Q1–2011Q1			1985Q1–2011Q1		
	PS	INV	UN	PS	INV	UN	PS	INV	UN
PS		0.15	0.02		0.13	0.10		0.22	0.10
INV	0.55		0.73	0.27		0.03	0.53		0.06
UN	0.00	0.10		0.40	0.63		0.44	0.65	

[a] Columns indicate the dependent variable, and rows the independent variables. The results reported here are for the VAR in (6) and the entries in the table give the p-values for the F-test of the null hypothesis that the all lags of the independent variable taken together do not Granger-cause the dependent variable. The VAR was estimated with 8 lags.

5.5 Summary

Bringing the results from IRFs, FEVDs and Granger Causality tests suggests the following interpretation. The FEVD shows that there is significant interaction among the three variables in the VAR: significant portions of the forecast error variance of each variable is explained by errors in other variables, especially when the forecast horizon increases beyond 8 quarters. The IRFs show that the pattern of dynamic interaction among the variables generates oscillating movement in each of the three variables. Moreover, this resul holds for three different "orderings" of the variables. The Granger causality test results, on the other hand, suggest that the direct effect of unemployment on profit share (in the sense of forecastability) is absent during the neoliberal period. On the other hand, the effect in the other direction, i.e., from profit share to unemployment, is weaker but still present in the neoliberal period. This suggests that the augmented CPS mechanism is still in operation under neoliberalism.

6 Conclusion

In this paper, we revisit the discussion about the relevance of the cyclical profit squeeze mechanism as an explanation for business cycle fluctuations under capitalism. Using quarterly data for the U.S. economy, we use a 3 variable VAR (cyclical deviations of unemployment rate, profit share and nonresidential fixed investment from their respective HP-filter trends) to summarize information about patterns of dynamic interactions among the variables. We find cyclical fluctuations in the impulse response functions during the regulated phase of post-War U.S. capitalism (1949Q4–1975Q1), as well as in the neoliberal phase (both 1980Q3–2011Q1 and 1985Q1–2011Q1). This finding runs counter to a strand in the literature which had suggested that the cyclical profit squeeze mechanism might have weakened, or completely disappeared, under neoliberalism.

We feel that the cyclical profit squeeze mechanism, as outlined by Marx in Volume I of *Capital*, rests on two-way interactions between the reserve army of labour (captured by the economy wide unemployment rate, for instance) and the share of income accruing to the capitalist. One side of this interaction runs directly from depleting reserve army (leading to rising bargaining power of labour)

Table 5: *Forecast Error Variance Decomposition: 1949Q4–1975Q1*[a]

	PSHARE			UNEMP			INVESTMENT		
	PS	INV	UN	PS	INV	UN	PS	INV	UN
1	1.00	0.00	0.00	0.21	0.13	0.67	0.25	0.75	0.00
2	0.97	0.01	0.03	0.32	0.09	0.59	0.38	0.59	0.03
3	0.85	0.07	0.08	0.35	0.08	0.57	0.46	0.51	0.02
4	0.75	0.14	0.11	0.37	0.07	0.55	0.46	0.52	0.02
5	0.51	0.22	0.27	0.36	0.11	0.54	0.46	0.52	0.02
6	0.42	0.20	0.38	0.31	0.18	0.50	0.43	0.48	0.09
7	0.39	0.20	0.41	0.25	0.23	0.52	0.35	0.42	0.23
8	0.37	0.19	0.43	0.20	0.26	0.54	0.29	0.38	0.33
9	0.37	0.20	0.43	0.18	0.27	0.55	0.24	0.39	0.36
10	0.35	0.22	0.44	0.18	0.27	0.55	0.22	0.40	0.37

[a] The results reported here are for the VAR in (6) estimated with 8 lags, and the entries in the table give percentage of the forecast error variance that is explained by each of the three variables in each column. The forecast horizon ranges from 1 to 10 quarters.

to the share of profit income; the other side of the interaction is mediated through the investment decisions of the capitalist class. While neoliberalism has weakened the relative bargaining position of labour vis-a-vis capital and has thereby weakened one side of the interaction, the other side has probably become stronger because of the ability of capitalists (certainly in the U.S.) to keep the size of the reserve army of labour large even during the recovery phase of business cycles. This issue deserves further investigation.

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Table 6: *Forecast Error Variance Decomposition: 1980Q3–2011Q1*[a]

	PSHARE			UNEMP			INVESTMENT		
	PS	INV	UN	PS	INV	UN	PS	INV	UN
1	1.00	0.00	0.00	0.04	0.20	0.76	0.01	0.99	0.00
2	0.98	0.00	0.02	0.09	0.24	0.67	0.06	0.92	0.02
3	0.95	0.01	0.04	0.11	0.26	0.63	0.09	0.86	0.05
4	0.90	0.06	0.04	0.11	0.29	0.60	0.09	0.81	0.10
5	0.82	0.14	0.04	0.13	0.25	0.61	0.10	0.76	0.14
6	0.71	0.25	0.04	0.14	0.23	0.63	0.13	0.69	0.18
7	0.62	0.35	0.03	0.16	0.23	0.61	0.16	0.65	0.20
8	0.58	0.39	0.03	0.17	0.25	0.57	0.17	0.63	0.20
9	0.56	0.41	0.03	0.19	0.29	0.53	0.18	0.64	0.19
10	0.55	0.42	0.03	0.19	0.32	0.49	0.18	0.65	0.17

[a] The results reported here are for the VAR in (6) estimated with 8 lags, and the entries in the table give percentage of the forecast error variance that is explained by each of the three variables in each column. The forecast horizon ranges from 1 to 10 quarters.

Table 7: *Forecast Error Variance Decomposition: 1985Q1–2011Q1*[a]

	PSHARE			UNEMP			INVESTMENT		
	PS	INV	UN	PS	INV	UN	PS	INV	UN
1	1.00	0.00	0.00	0.05	0.24	0.72	0.01	0.99	0.00
2	0.96	0.01	0.03	0.13	0.30	0.57	0.06	0.92	0.02
3	0.93	0.03	0.04	0.18	0.33	0.49	0.08	0.85	0.06
4	0.88	0.08	0.04	0.18	0.37	0.45	0.08	0.81	0.11
5	0.81	0.15	0.04	0.22	0.35	0.44	0.09	0.77	0.14
6	0.70	0.26	0.03	0.24	0.31	0.45	0.14	0.71	0.15
7	0.63	0.34	0.03	0.28	0.28	0.45	0.18	0.66	0.16
8	0.59	0.38	0.03	0.31	0.27	0.43	0.21	0.63	0.16
9	0.58	0.40	0.03	0.33	0.27	0.39	0.23	0.62	0.15
10	0.57	0.40	0.03	0.34	0.29	0.37	0.24	0.62	0.14

[a] The results reported here are for the VAR in (6) estimated with 8 lags, and the entries in the table give percentage of the forecast error variance that is explained by each of the three variables in each column. The forecast horizon ranges from 1 to 10 quarters.

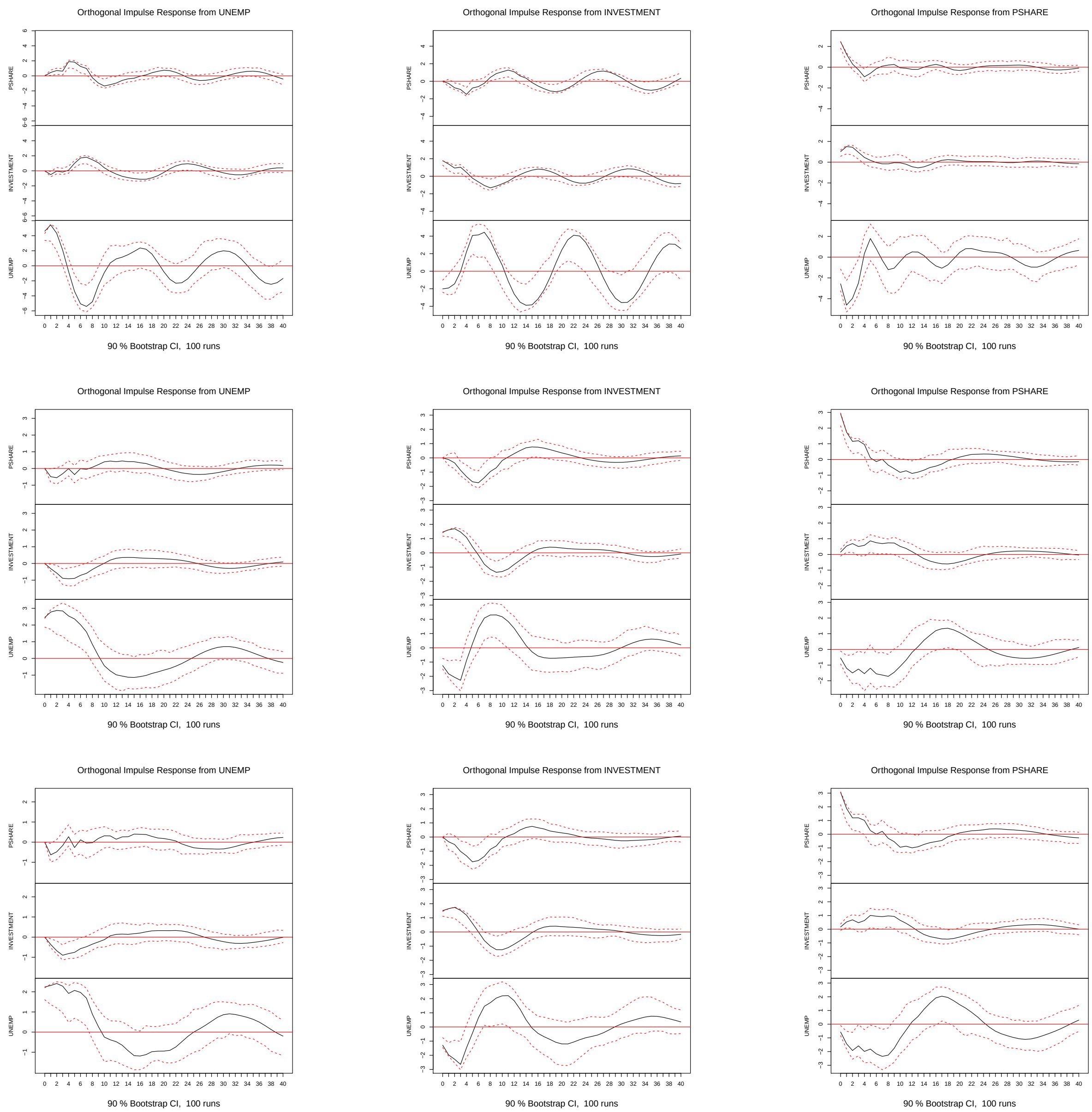

Figure 4: *Impulse Response Functions (with* 90 *percent confidence interval) from a* 3 *variable VAR for U.S., for three periods 1949Q4–1975Q1 (first row), 1980Q3–2011Q1 (second row), and 1985Q1–2011Q1 (third row). The variables are (1) PSHARE, which refers to the cyclical fluctuation of the profit share (corporate business sector) around its HP-filter trend; (2) UNEMP, which refers to cyclical fluctuation of the civilian unemployment rate around its HP-filter trend; and (3) INVESTMENT, which refers to the cyclical fluctuations of real nonresidential fixed investment around its HP-filter trend. Trends for each variable are computed for the whole period, 1948Q1–2011Q1. The order of the variables in the VAR is: PSHARE → INVESTMENT → UNEMP.*

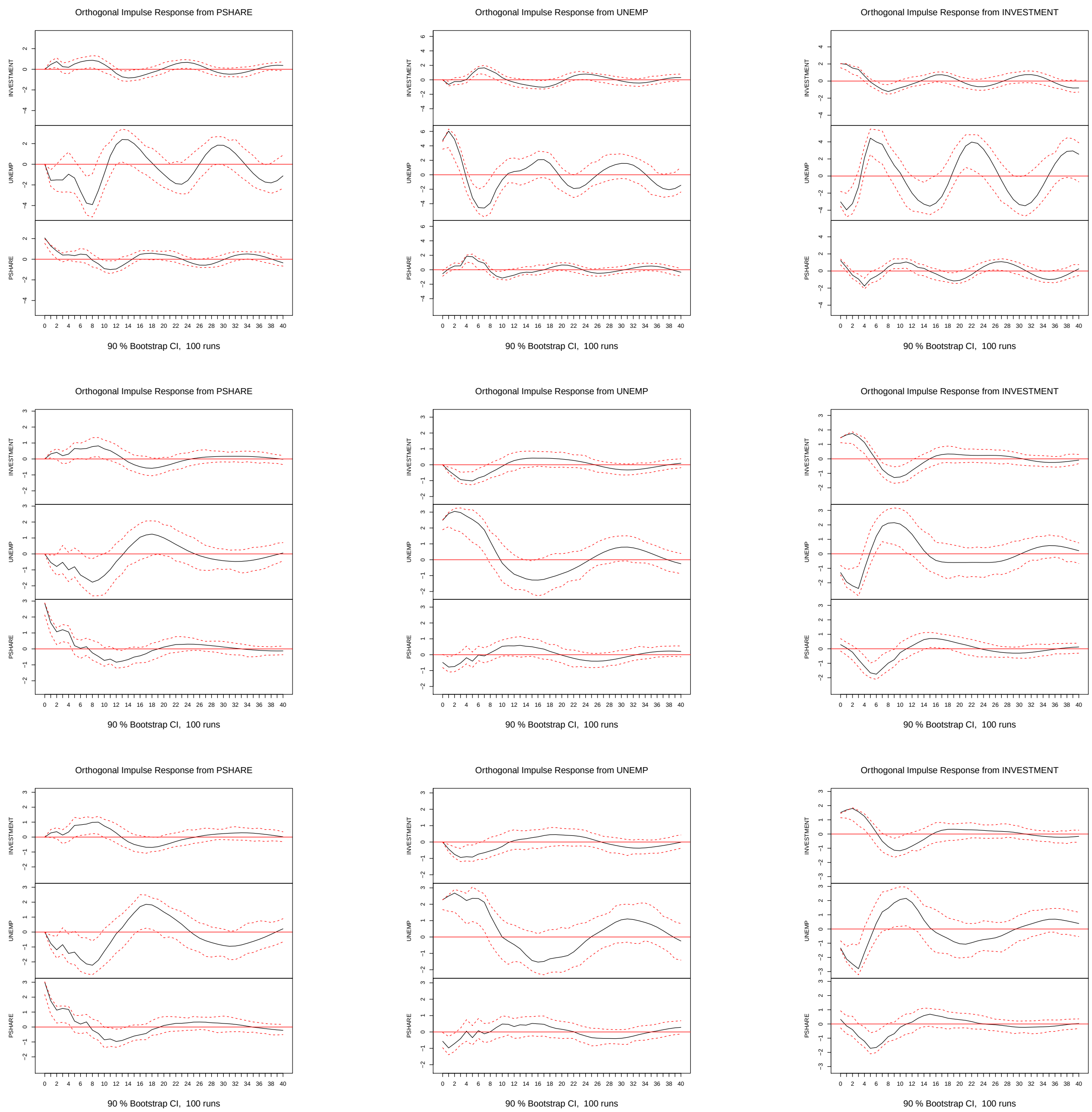

Figure 5: *Impulse Response Functions (with* 90 *percent confidence interval) from a* 3 *variable VAR for U.S., for three periods 1949Q4–1975Q1 (first row), 1980Q3–2011Q1 (second row), and 1985Q1–2011Q1 (third row). The variables are (1) PSHARE, which refers to the cyclical fluctuation of the profit share (corporate business sector) around its HP-filter trend; (2) UNEMP, which refers to cyclical fluctuation of the civilian unemployment rate around its HP-filter trend; and (3) INVESTMENT, which refers to the cyclical fluctuations of real nonresidential fixed investment around its HP-filter trend. Trends for each variable are computed for the whole period, 1948Q1–2011Q1. The order of the variables in the VAR is: INVESTMENT → UNEMP → PSHARE.*

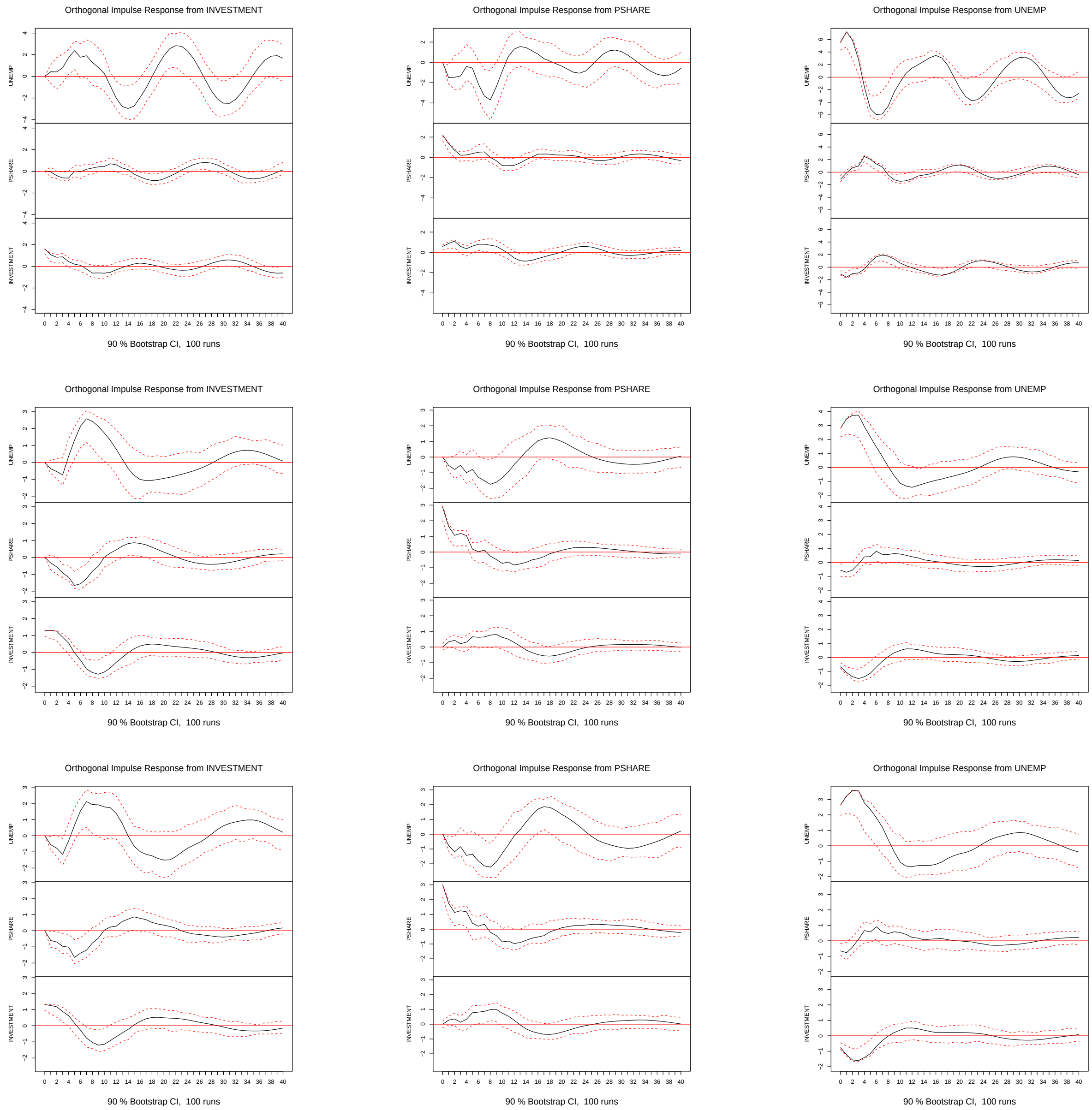

Figure 6: *Impulse Response Functions (with* 90 *percent confidence interval) from a* 3 *variable VAR for U.S., for three periods 1949Q4–1975Q1 (first row), 1980Q3–2011Q1 (second row), and 1985Q1–2011Q1 (third row). The variables are (1) PSHARE, which refers to the cyclical fluctuation of the profit share (corporate business sector) around its HP-filter trend; (2) UNEMP, which refers to cyclical fluctuation of the civilian unemployment rate around its HP-filter trend; and (3) INVESTMENT, which refers to the cyclical fluctuations of real nonresidential fixed investment around its HP-filter trend. Trends for each variable are computed for the whole period, 1948Q1–2011Q1. The order of the variables in the VAR is: UNEMP → PSHARE → INVESTMENT.*

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