Low Productivity Growth Causes Low Payroll Growth

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New York Times Irwin (2017), claimed that economists have a "chicken or egg problem": Did the recent low growth in productivity cause the slow growth of labor compensation, or the other way around? We use a newer R package 'generalCorr' H. D. Vinod (2017b), to determine the most plausible causal direction. It is based three sophisticated criteria.

Mason (2017) argues the liberal viewpoint while conservatives Cogan et al. (2017) claim productivity drought caused low labor compensation. See an earlier version of this at H. D. Vinod (2017a).

What do the post-war US data tell us?

Federal Reserve Bank (FRB) data used here.

```
load(file="c:/data/payprod.Rdata")
attach(data.frame(payprod))
payq=ts(payq,start=1947,frequency=4)
prod=ts(prod,start=1947,frequency=4)
rgdp=ts(rgdp,start=1947,frequency=4)
print(c(start(payq), start(prod), start(rgdp)))
```

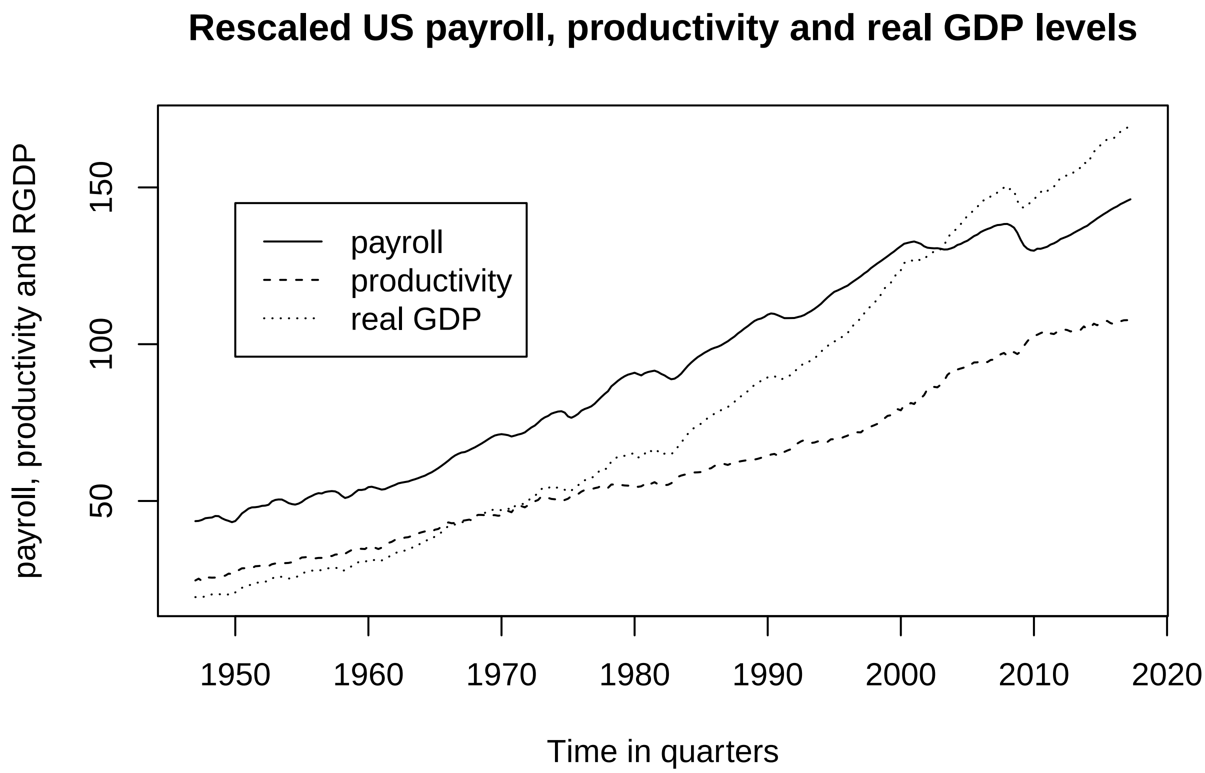
```
## [1] 1947    1 1947    1 1947    1
```

```
print(c(end(payq), end(prod), end(rgdp)))
```

```
## [1] 2017    2 2017    2 2017    2
```

The output shows that all three series start in the first quarter (Q1) of 1947 and end in Q2 of 2017. We rescale and plot data on payroll, productivity and real GDP for levels in the same figure. All three series are going up in the most recent three quarters.

```
ts.plot(payq, prod, rgdp,
        main="Rescaled US payroll, productivity and real GDP levels",
xlab="Time in quarters", ylab="payroll, productivity and RGDP", lty=1:3)
nam=c("payroll", "productivity","real GDP")
legend(x=1950,y=145,legend=nam, lty=c(1:3))
```



Causal paths between productivity and wage levels

Now we apply the methods in R package 'generalCorr', studied in Vinod (2015) and updated in H. D. Vinod (2017b) to assess which variables exhibit independent variation and which variables have dependent variation. That is, we assess which variable "kernel-causes" the other(s). Kernel causality is a compromise, and may not equal the true philosophical causality determined by double-blind controlled experiments in some natural sciences impractical here.

```
library(generalCorr)
options(np.messages=FALSE)
ss=causeSummary(cbind(payq, prod));ss
```

```
## [1] prod      causes    payq      strength= -31.496
## [1] corr=  0.9706 p-val= 0
```

```
##      cause  response strength corr.    p-value
## [1,] "prod" "payq"   "31.496" "0.9706" "0"
```

The above output shows that changes in productivity level induce changes in aggregate wage levels.

Computing growth rates and smoothing them.

What about the kernel causality between smoothed growth rates? Now compute percent growth rates from these data in levels, defined as $(y_{t+1} - y_t)/y_t$. This is done by defining an R function 'fn' and applying it to our data.

The following code lists the percent quarterly growth data (not annualized) for the latest six quarters, and also creates a graphical view of data in percent growth rates.

```
fn=function(Y){diff(Y)/ Y[-length(Y)]}
library(zoo)
payqGraw=(100*fn(payq))
prodGraw=(100*fn(prod))
print(tail(cbind(rawPay=as.zoo(payqGraw),
      rawProd=as.zoo(prodGraw)),8))
```

```
##            rawPay     rawProd
## 2015 Q3 0.4551558  0.32218601
## 2015 Q4 0.4931966 -0.64602610
## 2016 Q1 0.4263661 -0.29513173
## 2016 Q2 0.3553071  0.20767359
## 2016 Q3 0.4888147  0.61610308
## 2016 Q4 0.3523269  0.31222331
## 2017 Q1 0.3756593  0.03158971
## 2017 Q2 0.3371941  0.22941745
```

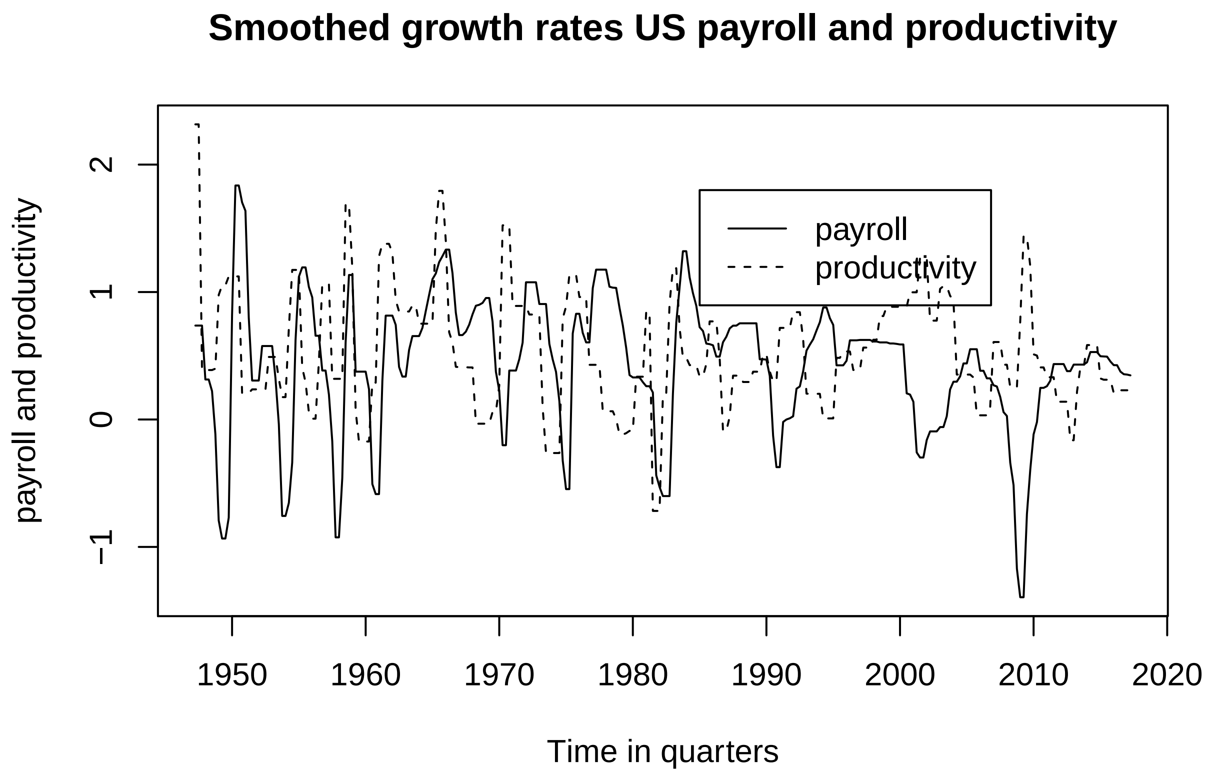
US had a negative productivity growth during Q1 and Q2 of 2016 and Q1 of 2017. Since the quarterly growth rates are not smooth, we apply Tukey's well known "3RS3R" smoother to represent slightly longer run behavior of the causal paths and also for less jagged plotting.

```
payqG=smooth(100*fn(payq))
prodG=smooth(100*fn(prod))
print(tail(cbind(pay=as.zoo(payqG),
      pro=as.zoo(prodG))))
```

```
##               pay       pro
## 2016 Q1 0.4263661 0.2076736
## 2016 Q2 0.4263661 0.2076736
## 2016 Q3 0.3756593 0.2294174
## 2016 Q4 0.3553071 0.2294174
## 2017 Q1 0.3523269 0.2294174
## 2017 Q2 0.3463665 0.2294174
```

Tukey's smoother equates the growth rates close to the median of nearby last three data points. It may represent longer run view and good for smoother plotting.

```
ts.plot(payqG, prodG,
        main="Smoothed growth rates US payroll and productivity",
xlab="Time in quarters", ylab="payroll and productivity", lty=1:2)
nam=c("payroll", "productivity")
legend(x=1985,y=1.8,legend=nam, lty=c(1:2))
```




```r
require(generalCorr);options(np.messages = FALSE)
ss=causeSummary(cbind(payqG, prodG));ss
```

```
## [1] prodG     causes    payqG     strength= -100
## [1] corr=   -0.0479 p-val=  0.4234

##      cause   response strength corr.     p-value
## [1,] "prodG" "payqG"  "100"    "-0.0479" "0.4234"
```

Results show smoothed productivity growth changes cause smoothed payroll growth changes.

Causal paths between raw growth rates

```r
ss=causeSummary(cbind(payqGraw, prodGraw));ss
```

```
## [1] prodGraw  causes    payqGraw  strength= -37.008
## [1] corr=   0.0845  p-val=  0.15776

##      cause      response   strength corr.    p-value
## [1,] "prodGraw" "payqGraw" "37.008" "0.0845" "0.15776"
```

Results show productivity growth changes cause payroll growth changes.

Causal paths after controlling for a variable.

We now illustrate an important ability of the 'generalCorr' package to remove the effect of potentially confounding variables by assigning them as 'ctrl' or control variables.

We can analogously define raw growth rate of real GDP and treat it as a control variable to see if the above causal path is reversed.

```
rgdpGraw=(100*fn(rgdp))
ss2=causeSummary(cbind(payqGraw, prodGraw),ctrl=rgdpGraw);ss2
```

```
## [1] prodGraw  causes    payqGraw  strength= -31.496
## [1] corr=   0.0845  p-val=  0.15776
```

```
##      cause      response   strength corr.    p-value
## [1,] "prodGraw" "payqGraw" "31.496" "0.0845" "0.15776"
```

It is interesting that the causal direction: (productivity)→(aggregate wage bill) is quite robust, since it remains true even after treating raw growth in real GDP as a potential confounder.

Conclusion: Data supports conservatives.

We have found a solution to the "chicken or egg problem" of macro economics identified by Irwin (2017) by using modern statistical tools described and simulated in Vinod (2015) with software in H. D. Vinod (2017b). We conclude that traditional economic theory and the conservative viewpoint is supported by the postwar US data. Our robustly estimated causal direction is: (productivity)→(aggregate wage bill), whether we use data in levels, growth rates or smoothed growth rates.

References

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