Seasonal Adjustment of NIPA data: Model-Based and Moving-Average-Based Approaches

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Outline of the talk

- Talk revisits two long-standing theoretical issues
  1. Model-based versus MA filters and choice of MA filter
  2. Seasonally adjusting aggregates or disaggregates

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- Applications will be to both NIPA and CES

Structure of Talk

1. Optimal filters
2. Issues with seasonally adjusting NIPA data

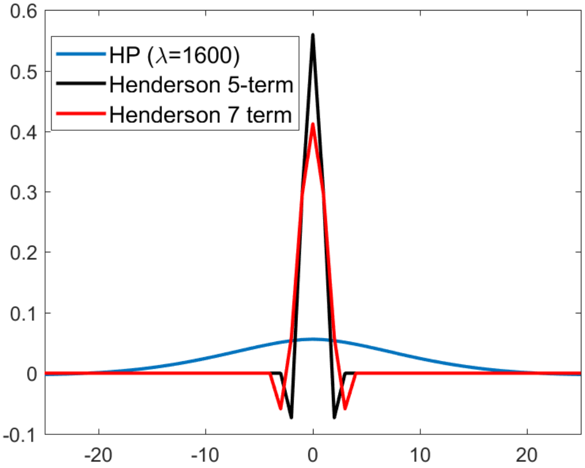
Parametric model

- TRAMO/SEATS specifies that data are the sum of 3 unobserved components:
    1. A trend T_t such that $\phi(L)\Phi(L^S)(1-L)^{d+D}T_t = \theta_T(L)\varepsilon_{Tt}$,
    2. A seasonal component, S_t, such that $(1+L...+L^{S-1})S_t = \theta_S(L)\varepsilon_{St}$ and,
    3. An irregular white noise process $N_t = \varepsilon_{Nt}$.
- Components are extracted from seasonal ARIMA
- Uses Kalman smoother to extract the 3 pieces
- Throughout use *canonical* decomposition

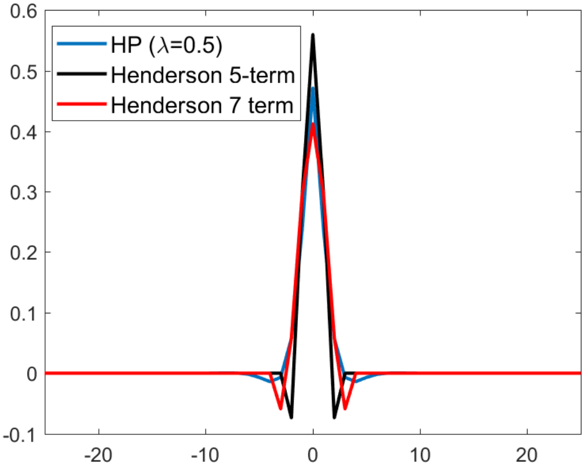
MA Filters: Trend

- X-11 uses either a 5- or 7-term trend Henderson filter with quarterly data
- Quite different from default HP filter, and rather consistent with Hamilton (2017)

MA Filters: Trend



MA Filters: Trend



SMA Filters

- Seasonal filter is 3x1 3x3 3x5 3x9 3x15 or stable
- Default choice is among 3x3 3x5 and 3x9 only

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- Seasonal filter is 3x1 3x3 3x5 3x9 3x15 or stable
- Default choice is among 3x3 3x5 and 3x9 only
- X-11 default applied to 150 CES series:

Filter	Number of Series
3x3	38
3x5	111
3x9	1

- Use just a little recent data.
  - Cyclical shocks distort seasonals.

Closest MA filter

- Could use MA, but pick filter to get minimize distance from parametric model.

$$i_1^* = \arg\min_i T^{-1}\Sigma_{t=1}^{T}(S_{SMA,i}(t) - S_M(t))^2$$

  - Cleveland and Tiao (1976), Burridge and Wallis (1984)
  - Depoutot and Planas (1998) give a lookup table
- Can optimize just SMA or both SMA and trend

Monte Carlo Simulation

- Explored different methods in a simple model
- Similar exercises done by Hood and Findley (1999), Hood (2002), Tiller, Chow and Scott (2007), Bell, Chu and Tiao (2011), Chu,Tiao and Bell (2012)
- DGP is:

$$(1-L)(1-L^{12})y_t = (1+\theta L)(1+\Theta L^{12})\varepsilon_t$$

Monte Carlo Simulation

- Sample Size is 120, and data are "monthly"
- As $\Theta \to -1$, seasonal gets more stable.
- Work out "true" seasonal component from the canonical decomposition
- Compare root mean square differences between true and estimated seasonal factors

RMSE of Alternative Seasonal Factor Estimates: Automatic Model Selection

θ	-0.3	-0.3	-0.3	-0.6	-0.6	-0.6	-0.9	-0.9	-0.9
Θ	-0.3	-0.6	-0.9	-0.3	-0.6	-0.9	-0.3	-0.6	-0.9
SEATS	0.09	0.09	0.21	0.07	0.08	0.20	0.09	0.11	0.21
X-11-Default	0.31	0.17	0.23	0.29	0.17	0.24	0.34	0.19	0.27
Optimal SMA	0.22	0.18	0.14	0.21	0.18	0.15	0.25	0.21	0.17
Optimal SMA and trend	0.20	0.17	0.14	0.19	0.17	0.14	0.23	0.20	0.17
Fixed Seasonal Moving Average Filters									
3x1	0.22	0.23	0.35	0.20	0.24	0.36	0.24	0.27	0.41
3x3	0.25	0.19	0.28	0.23	0.19	0.30	0.27	0.22	0.34
3x5	0.32	0.17	0.22	0.29	0.17	0.24	0.34	0.19	0.27
3x9	0.44	0.20	0.15	0.41	0.19	0.17	0.46	0.21	0.19
Stable	0.70	0.34	0.11	0.67	0.33	0.11	0.75	0.37	0.13

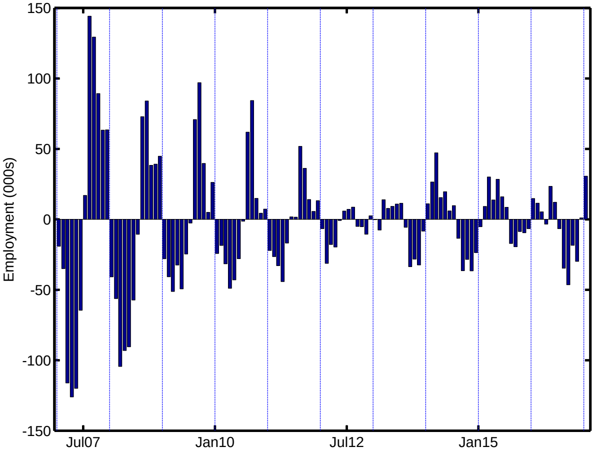
Monte Carlo Simulation: Conclusions

- Conclusions consistent with other literature
- Model-based does better than MA
- Default X-11 tends to be too short a window
- X-11 can get close in some cases
  - But not if Θ is close to zero
- Chu, Tiao and Bell (2012) report results less favorable to X-11 with uniform prior on white noise allocation.

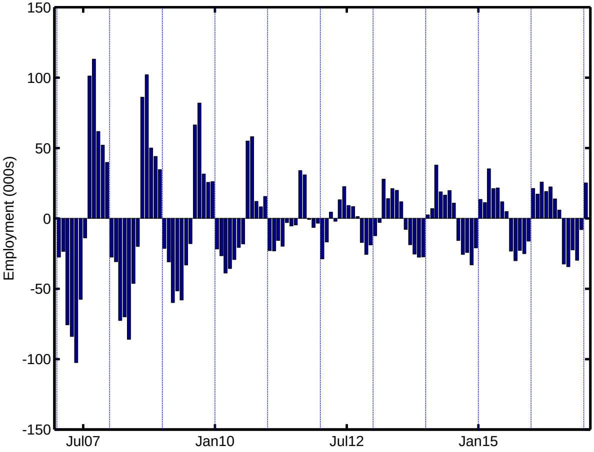
Application to CES data

- Replicated the seasonal adjustment in payrolls numbers
- Repeated with different seasonal adjustment methods, including SEATS and Optimal SMA and trend.

US Employment Data:  SA -  SA



US Employment Data: Optimal SMA/Trend Filter less Default X-11



Number of series for which optimal filter selected each filter option

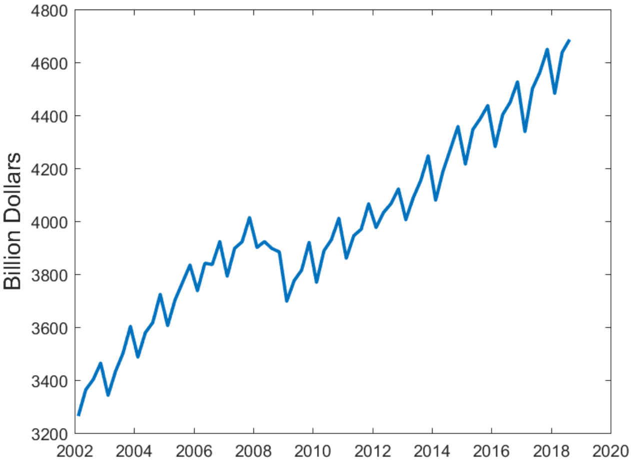
		Selecting Optimal SMA	Selecting Optimal SMA and Trend	X-11 Default
SMA	3x1	21	20	
	3x3	14	16	38
	3x5	24	24	111
	3x9	46	46	1
	Stable	45	44	
Trend	$m = 7$		78	
	$m = 9$		26	128
	$m = 13$		15	22
	$m = 17$		12	
	$m = 23$		9	
	$m = 33$		10	

- Preference for longer windows also found in Tiller, Chow and Scott (2007)

Window length

- US statistical agencies pick short rolling windows for seasonal adjustment.
- CES uses a 10 year rolling window.
- Seems odd, but not consequential with short filters.
- It is more consequential with optimal seasonal filters.

NSA Real GDP


Billion Dollars
4800
4600
4400
4200
4000
3800
3600
3400
3200
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020

Direct and indirect seasonal adjustment

- BEA uses *indirect* approach (disaggregates)
  - Benefit: SA data adds up
  - Cost: Residual seasonality
- Sources of residual seasonality
  1. Components not adjusted as no apparent seasonality
  2. Monthly series not adjusted as no apparent seasonality
  3. BEA policy does not adjust some series to make effects of policy clearer

Average quarterly data post 2002 Before 2018 revision

Quarter	Growth Rate
Q1	1.1
Q2	2.4
Q3	2.4
Q4	1.8

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- Weak Q1 pattern especially in federal defense spending

Is it significant?

- Let y_t be data and consider regression:

$$y_t = \alpha + \rho y_{t-1} + \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \varepsilon_t.$$

- Wald test of $\beta_1 = \beta_2 = \beta_3 = 0$
- Newey-West with lag truncation of $1.3T^{1/2}$ and "fixed b" critical values
- Like the standard X-13 F diagnostic but with different approach to HAC

Selected p-values: pre 2018 benchmark

Series	p-value
Real GDP	0.18
Structures	0.00
Fed Defense	0.05

- Similar mixed/borderline results obtained by Gilbert et al. (2015) and Lunsford (2017)

Monte-Carlo simulation (Calibrated to look like RGDP growth)

$$y_t = z_t + s_t$$

where

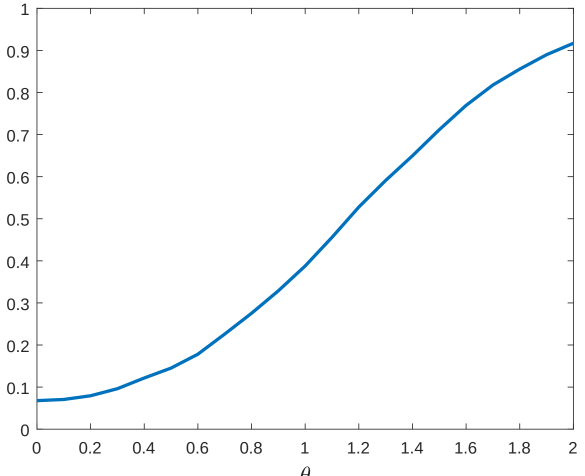
$$z_t = 0.4 z_{t-1} + \varepsilon_t,$$

ε_t is iidN(0,5) and

$$s_t = -\theta, t = 1, 5, 9, ..$$

$$s_t = \frac{\theta}{3}, \; t \neq 1, 5, 9, ..$$

Simulated Power Curve of Residual Seasonality Wald Test (T=64)



Size of Residual Seasonality Tests

- Data that we are applying these tests to have been seasonally adjusted
- That should make it unlikely to find seasonal patterns by chance alone
- Took Monte-Carlo simulation but for seasonality in X-13 adjusted data

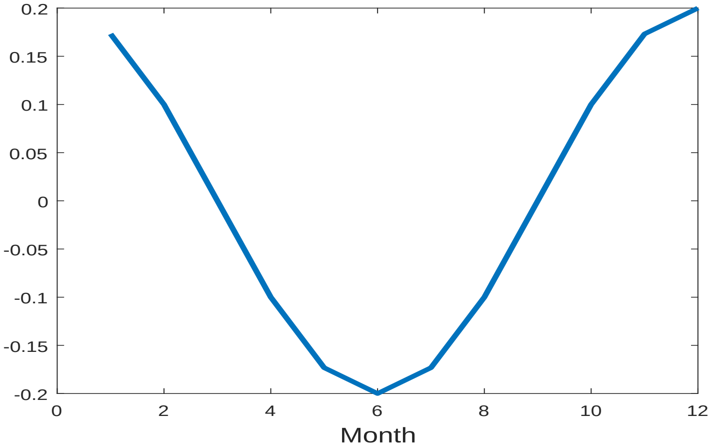
Size of Residual Seasonality Tests

	Effective Size (Nom=5%)
$\theta = 0.5$	0.003
$\theta = 1$	0.003
$\theta = 2$	0.004

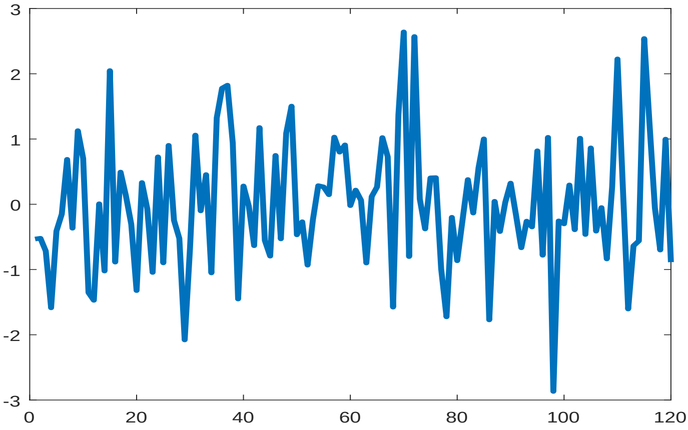
Simulation on Effects of Aggregation

- Generate 100 series each of which is Gaussian white noise plus a small stable seasonal
- 120 "monthly" observations for each series
- The same seasonal for each of the 100 components
- Consider 3 approaches for SA of the **sum** over these 100 components
  - Direct
  - Indirect
  - Indirect + Pretest (D8 F-test CV 7)

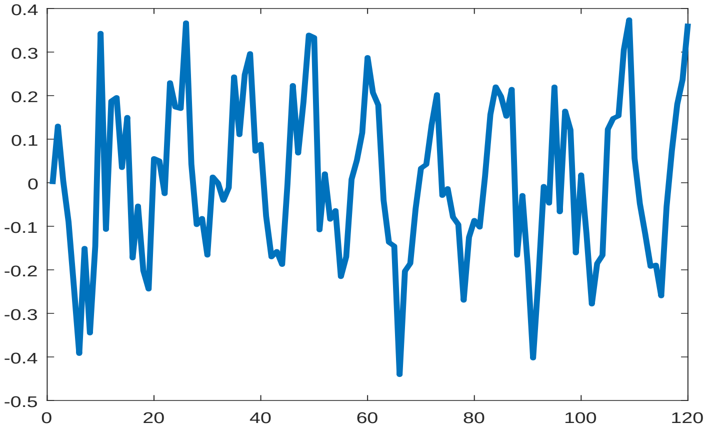
Deterministic Seasonal Pattern



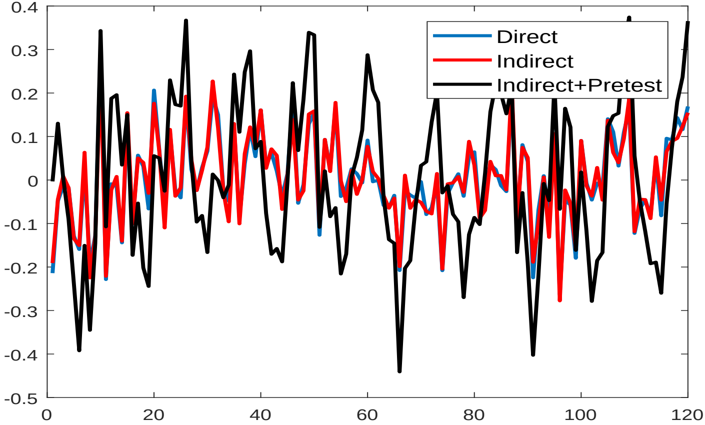
One of the 100 Disaggregates



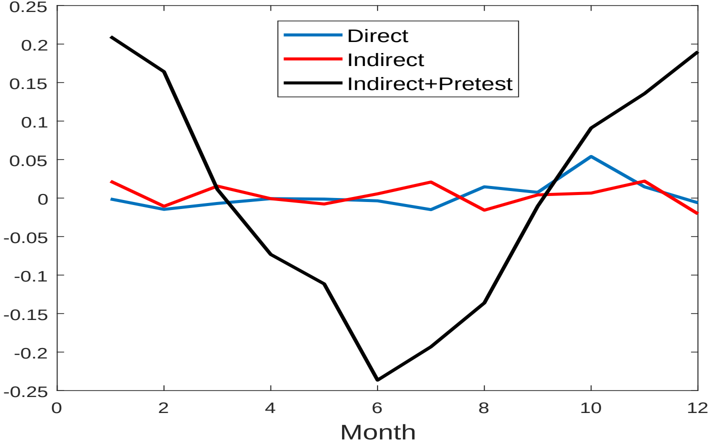
The Aggregate NSA Series



The Aggregate SA Series



The Aggregate SA Series: By month



Just an Illustrative Story

- Toy simulation
- Not calibrated to look like economic data
- Entirely common seasonal pattern
- Oversimplification of how decision (not) to seasonally adjust would be made

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- Toy simulation
- Not calibrated to look like economic data
- Entirely common seasonal pattern
- Oversimplification of how decision (not) to seasonally adjust would be made
- Point: Pretest+Aggregation+Correlation can cause a problem

Average quarterly data post 2002
After 2018 benchmark revision

Quarter	Growth Rate
Q1	1.5
Q2	2.4
Q3	2.2
Q4	1.9

Selected p-values: post 2018 benchmark

Series	p-value
Real GDP	0.66
Structures	0.00
Fed Defense	0.34

NIPA Seasonal Adjustment

- My preference is for direct seasonal adjustment
- Consider this via SEATS and X-13 on post 2002 data
- Intended as a proof-of-concept demonstration
  - Incorporate Easter and trading day effects
  - Automatic ARIMA model selection Gomez and Maravall
  - Default X-11 filter

Average quarterly data post 2002 Direct Seasonal Adjustment

Quarter	Growth Rate: X13	Growth Rate: SEATS
Q1	2.2	2.0
Q2	2.1	2.0
Q3	2.1	2.1
Q4	1.9	2.1

Average quarterly data post 2002 Direct Seasonal Adjustment

Quarter	Growth Rate: X13	Growth Rate: SEATS
Q1	2.2	2.0
Q2	2.1	2.0
Q3	2.1	2.1
Q4	1.9	2.1

- *p*-values overwhelmingly **insignficant**

Time-varying residual seasonality

- Evidence on residual seasonality sensitive to sample period (Moulton and Cowan (2016))
- BEA has applied different seasonal adjustment procedures over time
- Canova and Hansen (1995) offer test for time-varying seasonality

Time-varying residual seasonality: p vals

	BEA Pre-Rev	BEA Post-Rev	Direct SA: X13	Direct SA: SEATS
Real GDP	0.60	0.22	0.62	0.72
Consumption	0.02	0.07	0.53	0.76
Durables	0.01	0.03	0.71	0.69
Nondurables	0.25	0.30	0.06	0.66
Services	0.65	0.55	0.27	0.77
GPDI	0.61	0.50	0.83	0.58
Structures	0.21	0.18	0.36	0.41
Equipment	0.54	0.47	0.19	0.55
Int Prop	0.16	0.18	0.57	0.55
Residential	0.48	0.54	0.65	0.38
Exports	0.42	0.50	0.12	0.36
Imports	0.59	0.51	0.14	0.67
Government	0.28	0.54	0.53	0.73
Fed Defense	0.04	0.18	0.12	0.26
Fed Non Defense	0.27	0.51	0.70	0.52
State and Local	0.35	0.49	0.06	0.26
Price Indices				
GDP	0.07	0.23	0.31	0.45
PCE	0.14	0.13	0.09	0.04
Core PCE	0.14	0.72		

Real GDP Growth Rates in 2018

	BEA Pre-Rev	BEA Post-Rev	Direct SA: X13	Direct SA: SEATS
Q1	2.0	2.2	2.6	2.7
Q2		4.2	3.2	3.2
Q3		3.5	1.7	1.7

Selected first order autocorrelations

	BEA Pre-Rev	BEA Post-Rev	Direct SA: X13	Direct SA: SEATS
Real GDP	0.45	0.41	0.43	0.45
Consumption	0.60	0.51	0.67	0.86

Broader points and recommendations

- Statistical agencies should and do provide a single benchmark seasonal adjustment
- Key point is to make NSA data available so that researchers can make other choices
  - Until recently wasn't the case for NIPA

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- Statistical agencies should and do provide a single benchmark seasonal adjustment
- Key point is to make NSA data available so that researchers can make other choices
  - Until recently wasn't the case for NIPA
- My preference is for direct adjustment
  - If not, then adjust almost all disaggregates
- My preference is for model-based adjustment
  - If not, then longer filter