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Next Steps
Develop Coincident and Leading Indicator for Hawaiʻi:

Philly Fed CEI are based on a fixed set of indicators similar to conference board national coincident index:

- non-farm payroll employment
- unemployment rate
- hours in manufacturing
- real wage and salary disbursements
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Compare with Philadelphia CEI/LEI
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Evaluate usefulness of new CEI/LEI:
- Compare with Philadelphia CEI/LEI
- Evaluate turning point prediction
Key papers in literature which develops and evaluates regional CEI/LEI


Following the literature, we use the Kalman Filter to estimate a dynamic single-factor, multiple-indicator model.

\[ y_t = \alpha + \beta(L)s_t + \mu_t, \]  
\[ \phi(L)\mu_t = \epsilon_t, \]  
\[ \rho(L)s_t = \gamma + \eta_t, \]

where

- \( y_t \) is an \((nx1)\) vector of differenced logs of monthly indicators,
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Single Factor Model for Coincident Indicators

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- \(y_t\) is an \((nx1)\) vector of differenced logs of monthly indicators,
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- \(\mu_t\) is an \((nx1)\) vector of indicator idiosyncratic terms modeled as mutually uncorrelated AR processes.
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- \( \mu_t \) is an \((nx1)\) vector of indicator idiosyncratic terms modeled as mutually uncorrelated AR processes.
- and \( \epsilon_t, \eta_t \) are vector and scalar (assumed) white noise processes, respectively.
The Model
Assumptions and restrictions

\[ y_t = \alpha + \beta(L)s_t + \mu_t, \]  
\[ \phi(L)\mu_t = \epsilon_t, \]  
\[ \rho(L)s_t = \gamma + \eta_t, \]  

Assumptions/Restrictions:

The idiosyncratic error vector, \( \mu_t \) is modeled as an AR(2) process.
The Model
Assumptions and restrictions

\[ y_t = \alpha + \beta(L)s_t + \mu_t, \quad (1) \]
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The Model
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\[ y_t = \alpha + \beta (L) s_t + \mu_t, \quad (1) \]
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The idiosyncratic errors, and the error in the transition equation are restricted to have unit variance.
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Assumptions and restrictions

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We write the state space form by treating both equations (2) and (3) as the transition equation and including both \( \mu_t \) and \( s_t \) in the state vector.
The Model
Our State Space Form: Measurement Equation

\[
\begin{bmatrix}
y_{1t} \\
y_{2t} \\
y_{3t} \\
y_{4t}
\end{bmatrix} =
\begin{bmatrix}
0 & \beta_{11} & \phi_1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \beta_{21} & 0 & 0 & \phi_2 & 0 & 0 & 0 & 0 \\
\beta_{30} & 0 & 0 & 0 & 0 & \phi_3 & 0 & 0 & 0 \\
\beta_{40} & 0 & 0 & 0 & 0 & 0 & \phi_4 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
S_t \\
S_{t-1} \\
\mu_{1t} \\
\mu_{1,t-1} \\
\mu_{2t} \\
\mu_{2,t-1} \\
\mu_{3t} \\
\mu_{3,t-1} \\
\mu_{4t} \\
\mu_{4,t-1}
\end{bmatrix}
\]
The Model

Our State Space Form: Transition Equation

\[
\begin{bmatrix}
S_t \\
S_{t-1} \\
\mu_{1t} \\
\mu_{1,t-1} \\
\mu_{2t} \\
\mu_{2,t-1} \\
\mu_{3t} \\
\mu_{3,t-1} \\
\mu_{4t} \\
\mu_{4,t-1}
\end{bmatrix}
= \begin{bmatrix}
\rho_1 & \rho_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & d_{11} & d_{12} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & d_{21} & d_{22} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & d_{31} & d_{32} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & d_{41} & d_{42} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
S_{t-1} \\
S_{t-2} \\
\mu_{1,t-1} \\
\mu_{1,t-2} \\
\mu_{2,t-1} \\
\mu_{2,t-2} \\
\mu_{3,t-1} \\
\mu_{3,t-2} \\
\mu_{4,t-1} \\
\mu_{4,t-2}
\end{bmatrix}
+ \begin{bmatrix}
\eta_t \\
\epsilon_{1t} \\
\epsilon_{2t} \\
\epsilon_{3t} \\
\epsilon_{4t}
\end{bmatrix}
\]
A first reaction to the Philadelphia Fed indicators. Are hours in manufacturing really useful in forming a CEI for Hawaiʻi:

**Figure:** Manufacturing vs Non-farm Jobs

**Figure:** Manufacturing Hrs. vs Non-farm Jobs
## The Data

### Choice of Indicators

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Employees on non-agricultural payrolls</td>
<td>Employees on non-agricultural payrolls</td>
<td>Employees on non-agricultural payrolls</td>
</tr>
<tr>
<td>Real personal income minus transfer payments (monthly)</td>
<td>Real wage &amp; salary disbursements (quarterly)</td>
<td>Real wage &amp; salary disbursements (interpolated)</td>
</tr>
<tr>
<td>Real manufacturing and trade sales</td>
<td>Avg. hours worked in manufacturing</td>
<td>Visitor arrivals</td>
</tr>
<tr>
<td>Industrial production</td>
<td>Unemployment rate</td>
<td>Unemployment rate</td>
</tr>
</tbody>
</table>

### Model 1
- Real withholding tax revenue instead of wage & salary disbursements
- Real General Excise tax base instead of visitor arrivals

### Model 2
- Real withholding tax revenue instead of wage & salary disbursements
- Real General Excise tax base instead of visitor arrivals
Sample starts in January of 1982 and runs through July 2017 (model 1), or January 2018 (model 2) after smoothing.
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In Model 1, in place of indicators for Manufacturing, we use Visitor Arrivals.

In Model 2, we use monthly tax data instead of the interpolated real wage and salary disbursements. Excessive noise and outliers in the tax series lead us to use a 13 month centered moving average for smoothing.

Nominal series are deflated using the US Consumer price index, the Honolulu CPI history is predominantly semiannual. Similar to the Philadelphia state CEI models, we use non-farm payroll employment and the unemployment rate.
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Similar to the Philadelphia state CEI models, we use non-farm payroll employment and the unemployment rate.
The Data
Model 1

Smoothed vs. Unsmoothed Employment (MA13)

Unemployment rate

Smoothed vs. Unsmoothed Wages (MA13)

Smoothed vs. Unsmoothed Visitor arrivals (MA13)
The Data
Model 1: retrended and scaled

Coincident indicators, retrended and scaled to Employment

Indicators
- Employment
- Unemployment
- Visitor Arrivals
- Wages
The Data
Model 2

Smoothed vs. Unsmoothed Employment (MA13)

Unemployment rate

Smoothed vs. Unsmoothed TGB (MA13)

Smoothed vs. Unsmoothed Income tax (MA13)
The Data
Model 2: retrended and scaled

Coincident indicators, retrended and scaled to Employment

Indicators
- Employment
- Income tax
- TGB
- Unemployment
## Results

### Model 1: Coefficient Estimates

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Employment</th>
<th>Unemployment</th>
<th>Wages</th>
<th>Visitors</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$</td>
<td></td>
<td></td>
<td><strong>0.0191</strong></td>
<td><strong>0.0066</strong></td>
</tr>
<tr>
<td>$\beta_1$</td>
<td><strong>0.0274</strong></td>
<td><strong>-0.0177</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi$</td>
<td><strong>-3.27e-7</strong></td>
<td>3.70e-4</td>
<td><strong>-2.79e-5</strong></td>
<td><strong>-2.35e-7</strong></td>
</tr>
<tr>
<td>$d_1$</td>
<td><strong>-0.1950</strong></td>
<td>0.0017</td>
<td>0.0060</td>
<td>0.0706</td>
</tr>
<tr>
<td>$d_2$</td>
<td><strong>0.3592</strong></td>
<td><strong>0.0111</strong></td>
<td>0.220</td>
<td><strong>0.0080</strong></td>
</tr>
</tbody>
</table>

Autoregressive coefficients for the state variables

| $\rho_1$  | 1.8519 |
| $\rho_2$  | -0.8574 |
Results
Model 1: Normalized Index
Results
Model 1: re-trended and scaled to real GSP
### Results

#### Model 2: Coefficient Estimates

<table>
<thead>
<tr>
<th>Coef.</th>
<th>Employment</th>
<th>Unemployment</th>
<th>GE Tax Base</th>
<th>Withholding Tax</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$</td>
<td>0.0274</td>
<td>-0.0174</td>
<td>0.0091</td>
<td>0.0070</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.0041</td>
<td>-0.3948</td>
<td>0.1488</td>
<td>0.5636</td>
</tr>
<tr>
<td>$\phi$</td>
<td>4.83e-5</td>
<td>3.35e-7</td>
<td>-2.59e-7</td>
<td>2.62e-8</td>
</tr>
<tr>
<td>$d_1$</td>
<td>0.0022</td>
<td>0.0376</td>
<td>0.4029</td>
<td>-0.0698</td>
</tr>
<tr>
<td>$d_2$</td>
<td>0.0022</td>
<td>0.0376</td>
<td>0.4029</td>
<td>-0.0698</td>
</tr>
</tbody>
</table>

**Autoregressive coefficients for the state variables**

| $\rho_1$ | 1.8556 |
| $\rho_2$ | -0.8608 |
Results
Model 2: Normalized Index

Normalized Index vs. Indicators

- Index
- Employment
- Income tax
- Index
- TGB
- Unemployment
Results
Model 2: retrended and scaled to real GSP

De-normalized Index vs. Indicators

Indicators
- CEI
- Employment
- GSP
- Income tax
- TGB
- Unemployment
Results
Comparing CEI

Model 1 (2012M1 = 100)
Philly Fed CEI
Model 2 (2012M1 = 100)

[Graph showing trends and comparisons]
Lots of work left to be done

Data cleaning and smoothing.
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Model quarterly income as monthly series.
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Explore optimal variance for added noise when dealing with corner solutions.
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Test for single factor and explore specification.
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Data cleaning and smoothing.

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Explore optimal variance for added noise when dealing with corner solutions.

Test for single factor and explore specification.

Once satisfied with CEI, move on to LEI and evaluate.