Could a large scale asset purchase programme have mitigated the Great Depression

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Outline

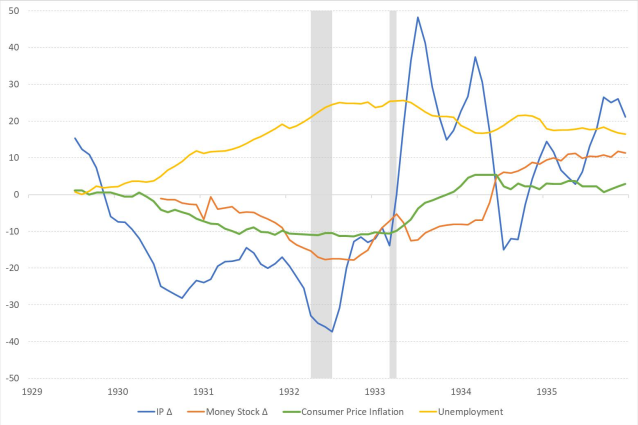
- Recent financial crisis: unconventional monetary policy measures
  - Large scale asset purchase programs
  - Sharp interest rate ↓ (towards effective ZLB)
- **What would have been the impact of more aggressive monetary policy during the Great Depression?**
  - Bayesian VAR to estimate forecasts conditional on alternative policy paths
- Contrast with recent policy:
  - Gold standard
    - Temin (1976): Fed limited in what it could do
    - Hsieh and Romer (2006), Bordo et al., (1999): perhaps not limited
  - No announcement
    - No explicit forward guidance

Historical Context

- Banking Act 1932
  - Changed proportion of gold required to back notes
  - Thus freeing gold reserves
- February 1932
  - OMPC authorised purchases of government securities
- July 9, Gov. McDougal of Chicago Fed:
  - "...we believe that the additional purchases made were much too large and have resulted in creating abnormally low rates for short-term US Government securities."

Macroeconomy

- Higlighted bars: Purchase period (April-July 1932), 'Roosevelt bank holiday' (March/April 1933)
  - '**Double Bottom**' (Burns and Mitchell, 1946)



Policy

- Fed's role during Great Depression has been criticised:
  - Little to mitigate effects of crisis
  - No prevailing wisdom about how to respond to downturn
  - Although **official rates** were reduced at start of crisis
    - Never reached ZLB
    - Even were raised in late 1931 and early 1932 in response to strong outflows of gold after Britain abandoned gold standard
  - Government bond **purchase program**: limited in time
- Instead, **Roosevelt's 'bank holiday'** in March/April 1933 and effective devaluation of dollar

Data

- Monthly data: 1919M1-1934M7
- Data set tries to mimic what Fed would have looked at as most likely to influence policy (Iversen et al., 2014)
  - Federal Reserve Bulletins: National Summary of Business Conditions
- Data sources: Fred, Alfred, Fraser, NBER historical database, Shiller

Data Categories

1. **Prices**
   - CPI, PPI, wholesale price fuel and lighting
2. **Business cycle**
   - Industrial production, department store sales
3. **Labour market**
   - Factory employment, factory earnings
4. **Financial variables**
   - Money stock, S&P composite stock price index, yield spread (10y - 3m), exchange rate with Swiss Franc
5. **Stress measures**
   - Liabilities of commercial business failures, spread (Baa-rated corporate bonds and LT govt bonds), spread between secured and unsecured money market rates
6. **Monetary policy variables**
   - Fed purchases of government securities, NY Fed discount rate

Large Bayesian VAR Model

- **Large Bayesian VAR**
  - 17 variables, 12 lags
  - Core variables + labour, financial, external and monetary variables
    - Gambacorta et al. (2014): need to capture spillovers between real economy and financial markets
- Gains from large Bayesian VARs (De Mol et al., 2008):
  - Estimation through shrinkage of parameters
- **Dummy observation prior** (Banbura et al., 2010) Dummy Obs
  - Allows us to match Minnesota moments and integrate sum of coefficients Prior
    - Consistent with unit root or cointegration processes

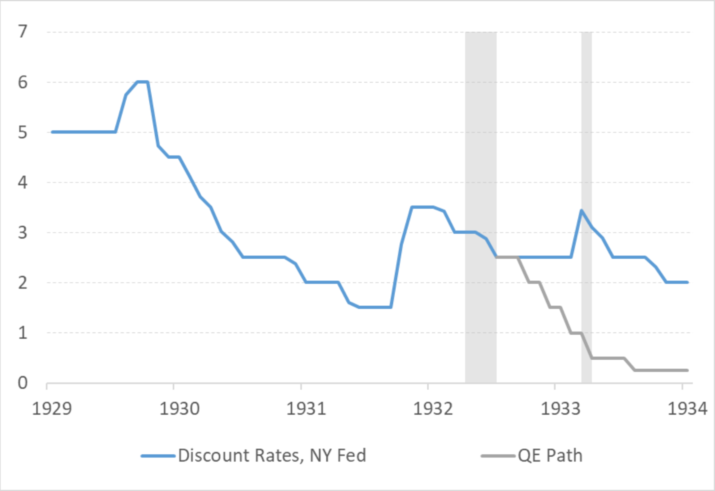
Large Bayesian VAR Model

- Desire to include many macro variables (Gambacorta et al., 2014) $\rightarrow$ **"Curse of dimensionality"**
  - Uncertainty, financial turmoil and economic risk variables to unravel exogenous changes in CB balance sheet from endogenous intervention
- Quick proliferation of parameters that have to be reliably estimated in large dimensional systems
  - Trade-off between
    - Misspecification and forecast accuracy
    - Issues of collinearity and overfitting
- High number of parameters cannot be well estimated by ML/OLS,
  - Recent developments in macroeconometrics $\rightarrow$ 2 approaches able to deal with this complexity:
    - **Bayesian VARs** and dynamic factor models (Banbura et al., 2014)

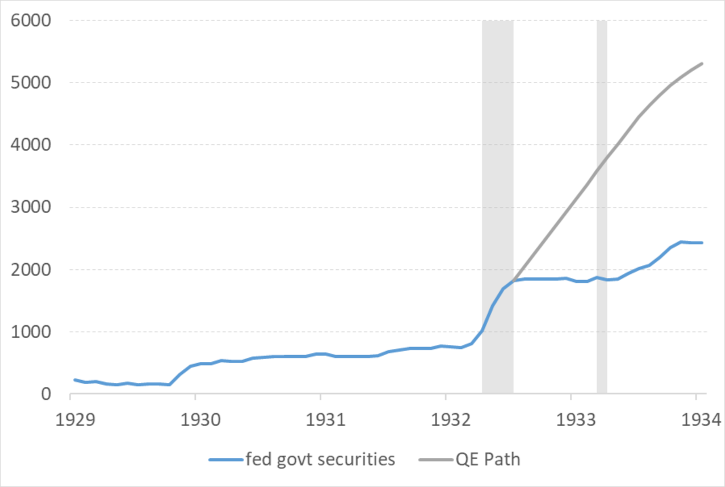
Scenario Analysis

- **Conditional forecasting methodology** (Waggoner and Zha, 1999)
  - Many policy applications: ▸ Conditional Forecasting
    - Bloor and Matheson (2009), Beauchemin and Zaman (2011), Tallman and Zaman (2012), Baumeister and Benati (2012), Kapetanios et al. (2013), Giannone et al. (2014), Jarocinski and Bobeica (2016), Wieladek and Garcia Pascual (2016)
- **Government securities purchased April - July 1932: $121 million to $399 million per month**
  - **Our path: 12 more months at $220 million per month (Aug 1932 to July 1933)**
    - Taper for 6 months until just $105 million of purchases are made in January 1934
  - **Reduction in NY Fed discount rate from 2 percent (Aug 1932) to 0.25 percent in (Aug 1933)**

Path 1: NY Fed Discount Rate

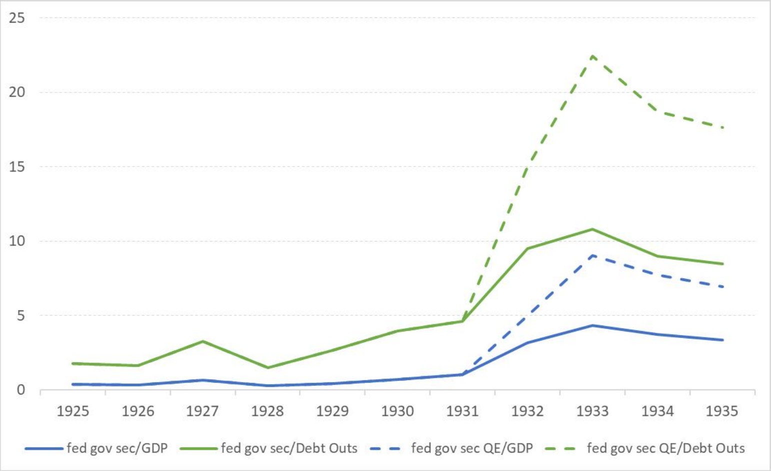


Path 2: Fed Purchases of Gov Securities

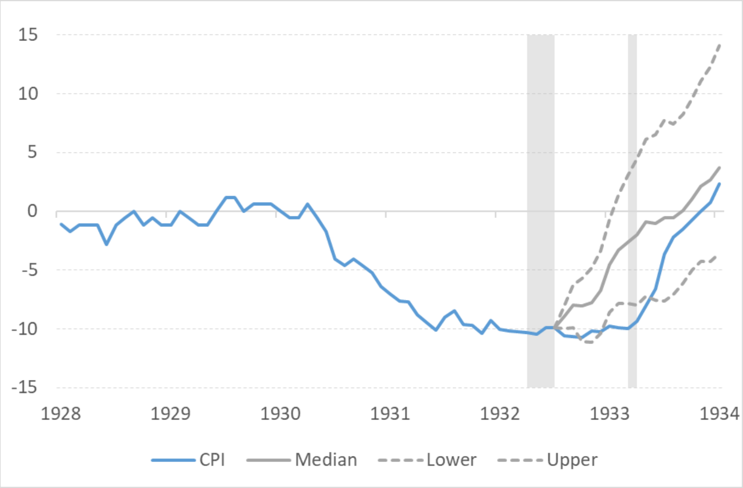


▸ Historical Purchases

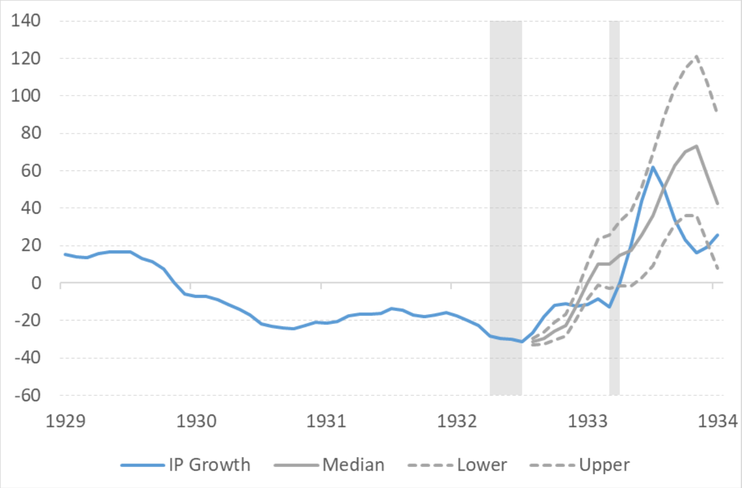
Relative Size of Purchases



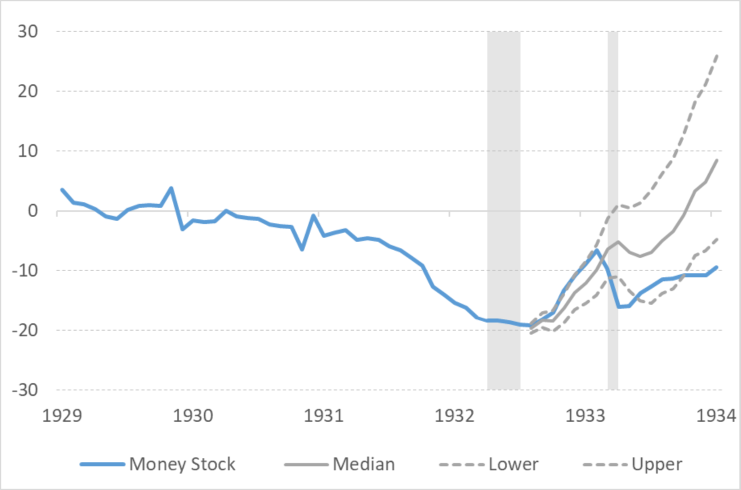
Consumer Price Inflation



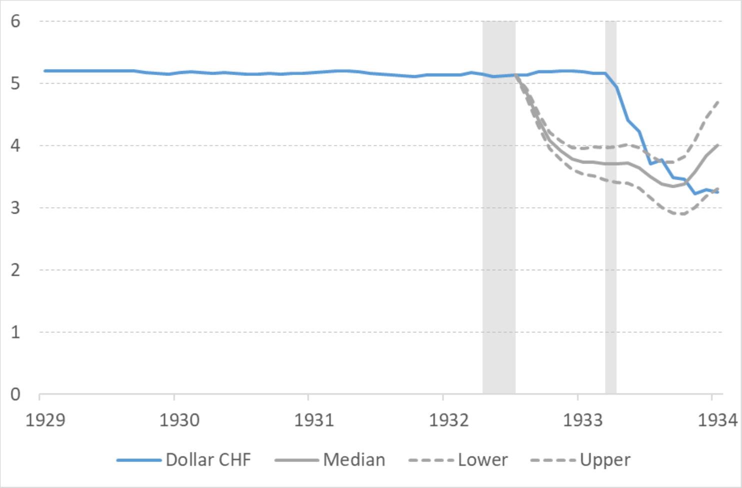
Industrial Production Growth



Money Stock Growth



Exchange Rate



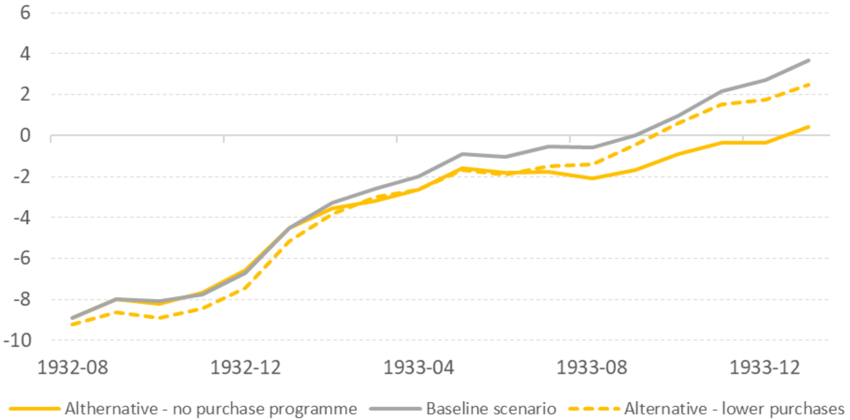
Additional Results

Alternative Scenario

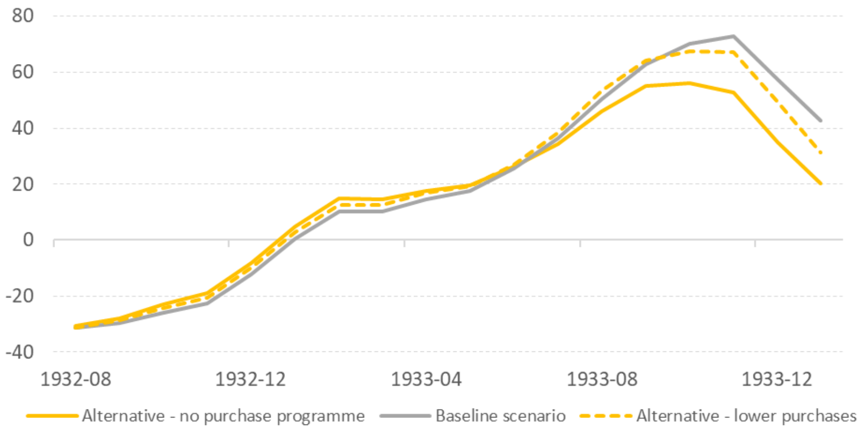
- To test whether **extending the purchase programme** really mattered, we analyse several alternative scenarios:

  1. No asset purchases, only the prior interest rate cut
  2. Smaller asset purchase programme, and the prior rate cut:
     - $180million per month for 12 months (previously $220)
     - Tapering for 6 months: $65 million in the final month

CPI Inflation, Alternative Scenario



IP Growth, Alternative Scenario



Conclusion

- More expansionary monetary policy could have eased the Great Depression
  - **Positive growth in prices and output sooner**
- Federal Reserve could have significantly improved economic outcomes
  - Both **purchases of government securities** as well as the interest rate drop are instrumental
  - But would have increased the money supply substantially
- Large impact on the **exchange rate**

Minnesota Prior

- Minnesota prior for coefficients can be retrieved by setting following moments (Blake and Mumtaz, 2012)

$$E\left[(A_k)_{ij}\right] = \begin{cases} \delta_i & j=i,\ k=1 \\ 0 & otherwise \end{cases},\ V\left[(A_k)_{ij}\right] = \begin{cases} \frac{\lambda^2}{k^2} & j=i \\ \vartheta\frac{\lambda^2}{k^2}\frac{\sigma_i^2}{\sigma_j^2} & otherwise \end{cases} \quad (2)$$

- Coefficients $A_1, \ldots, A_p$ considered independent and normally distributed
- δ_i : prior coefficient mean for first lag of dependent variables

Minnesota Prior

- Hyperparameter λ: general tightness of prior distribution around random walk or white noise component
- $1/k^2$: rate at which prior variance decreases when lag length increases
- Ratio $\frac{\sigma_i^2}{\sigma_j^2}$ takes into account differences in scale of data
- Coefficient $\vartheta \in (0,1)$ characterizes the extent to which lags ofother variables are 'less important' than own lags
- Covariance matrix of residuals is considered to be diagonal, fixed and known
  - $\Psi = \Sigma$, with $\Sigma = diag\left(\sigma_1^2, \ldots, \sigma_n^2\right)$
- Prior on intercept is diffuse

▸ BVAR

Dummy Observation Prior

- Following Banbura et al (2010), we implement dummy observation prior by appending T_d dummy observations, as expressed in Y_d and X_d, to the system:
  - Where coefficients have normal prior and covariance matrix has normal inverted Wishart prior: $vec(B)|\Psi \sim N(vec(B_0), \Psi \otimes \Omega_0)$, $\Psi \sim iW(S_0, \alpha_0)$.

$$Y_d = \begin{pmatrix} diag(\delta_1\sigma_1, \ldots, \delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ \ldots\ldots\ldots\ldots \\ diag(\sigma_1, \ldots, \sigma_n) \\ \ldots\ldots\ldots\ldots \\ 0_{1\times n} \end{pmatrix} \quad X_d = \begin{pmatrix} J_p \otimes diag(\delta_1\sigma_1, \ldots, \delta_n\sigma_n)/\lambda & 0_{np\times 1} \\ \ldots\ldots\ldots\ldots & \\ 0_{n\times np} & 0_{n\times 1} \\ \ldots\ldots\ldots\ldots & \\ 0_{1\times np} & c \end{pmatrix} \quad (3)$$

  - with $J_p = diag(1, 2 \ldots, p)$.

Dummy Observation Prior

- Different segments:
  - First block of dummies represents the prior beliefs on the AR coefficients
  - Second block summarizes prior for the covariance matrix
  - Third block describes the uninformative prior for the intercept
- We retrieve required structures Y^* and X^* by adding dummies Y_d and X_d to the original data:

$$Y^* = [Y, Y_d], \; X^* = [X, X_d] \quad (4)$$

- Using this appended data, the conditional distributions can be integrated in the Gibbs sampling algorithm
  - Results are based on 15000 draws from the Gibbs sampler, with a burn-in of 10000

▸ BVAR

Conditional Forecasting

- "**Conditional-on-observables**" (Banbura et al., 2015)
  - Outcome for macro-financial variables, given path for policy rate and purchases
  - What would have happened if Fed continued purchases at every point
    - Hsieh and Romer (2006)
- Alternatively, what would happen if there was a series of MP surprises at each point
  - "**Structural scenario analysis**"
  - (Antolin-Diaz et al., 2018)

Scenario Analysis

Conditional Forecasting

- Consider a VAR(1) model (Blake and Mumtaz, 2014):

$$Y_t = c + BY_t + A_0\varepsilon_t \quad (5)$$

- with Y_t representing a $T \times N$ matrix of endogenous variables
  - ε_t denoting the uncorrelated structural shocks
  - $A_0 A_0^{'} = \Sigma$.
    - Σ represents the variance of the reduced VAR residuals
- When we iterate equation (5) K times forward, we retrieve

$$Y_{t+K} = c \sum_{j=0}^{K} B^j + B^j Y_{t-1} + A_0 \sum_{j=0}^{K} B^j \varepsilon_{t+K-j} \quad (6)$$

Conditional Forecasting

- Hence, when we place restrictions on future path of J^{th} variable in Y_t, this also induces restrictions on other variables in system
  - If we re-structure equation (6) this becomes more visible:

$$Y_{t+K} - c\sum_{j=0}^{K} B^j - B^j Y_{t-1} = A_0 \sum_{j=0}^{K} B^j \varepsilon_{t+K-j} \quad (7)$$

- When we constrain some of variables in dataset to fixed path, this means that future innovations on right hand side of equation will have restrictions as well.
  - These constraints on future innovations are defined in Waggoner and Zha (1999) as:

$$R\varepsilon = r \quad (8)$$

Conditional Forecasting

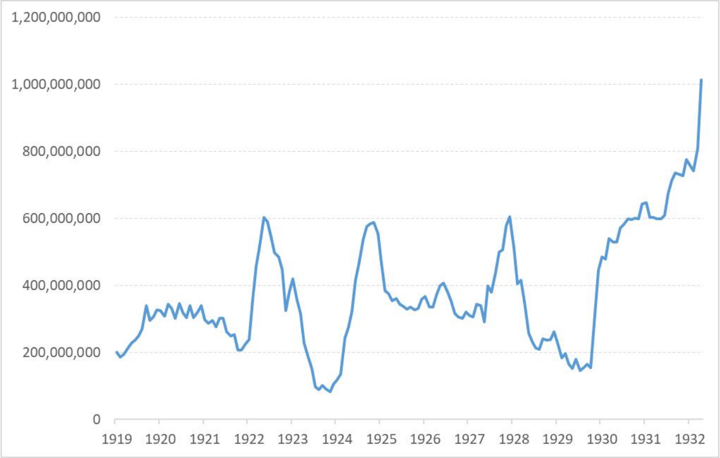
- Elements of r contain path for constrained variables minus unconditional forecasts of constrained variables.
  - Elements of matrix R are impulse responses of constrained variables to structural shocks ε over desired forecasting horizon
  - A least square solution for constrained shocks in (8) is given by Doan et al. (1983):

$$\varepsilon = R' \left(R'R\right)^{-1} r \quad (9)$$

- Inserting these constrained innovations in equation (5) allow us to calculate conditional forecasts

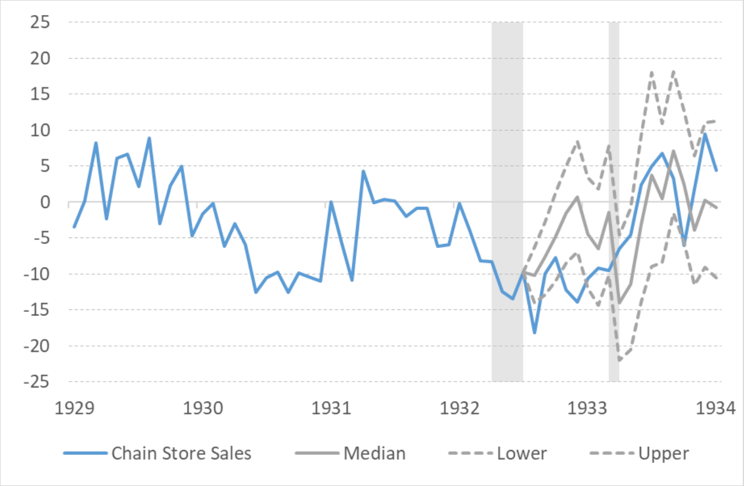
Scenario Analysis

Historical Gov Securities Purchases

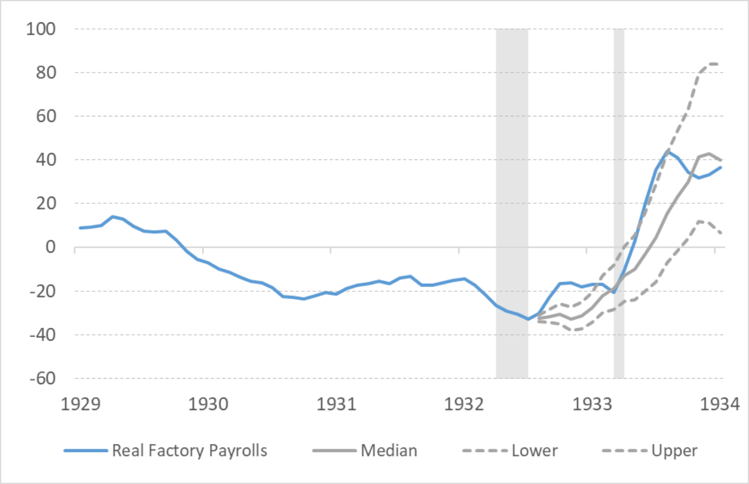


▸ Path Purchases

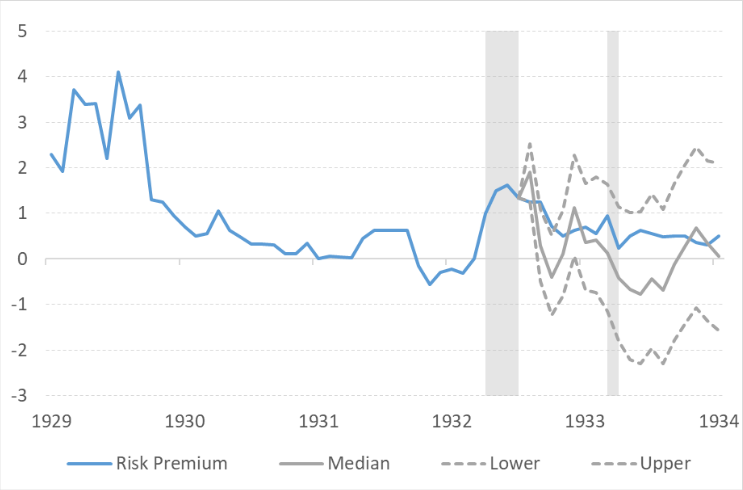
Retail Sales Growth



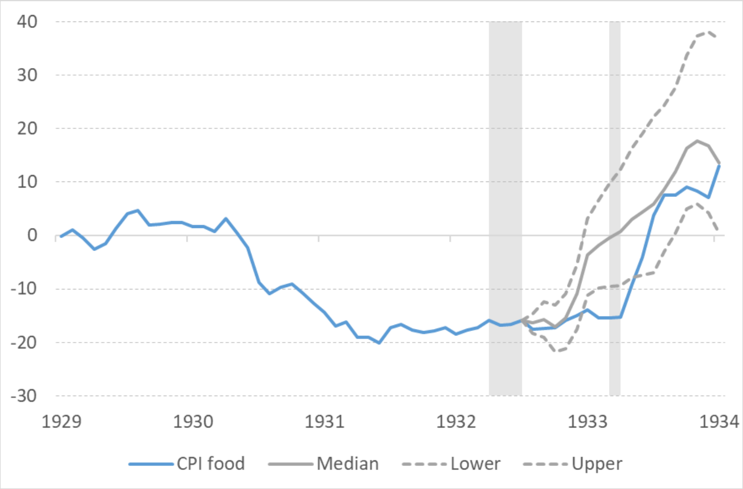
Real Wage Growth



Risk Premium



Food Price Inflation



Alternative Scenario