Web-appendix (not for publication):

Evaluating Policy Institutions

–150 Years of US Monetary Policy–

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Abstract

In this web-appendix we provide the following additional results:

S1 Role of news shocks

S2 Implementation guide

S3 Additional empirical results

S4 A proxy for monetary policy shocks from large gold mine discoveries, 1879-1912

S1 Role of news shocks

Recall that Lemma 1 in the main text implies

$$\mathbf{Y} = \Gamma(\phi,\theta)\boldsymbol{\Xi} + \mathcal{R}(\phi,\theta)\boldsymbol{\epsilon}\ , \tag{S1}$$

where $\boldsymbol{\epsilon} = (\epsilon_0', \epsilon_1', \ldots)'$ and $\boldsymbol{\Xi} = (\xi_0', \xi_1', \cdots)'$ are sequences of policy and non-policy shocks, respectively. This shows that in order to identify Γ and $\mathcal{R}$ we require knowledge of the current ϵ_0, ξ_0 and future shocks ϵ_h, ξ_h for $h \geq 1$.

Is useful to clarify that in practice this requires the identification of news shocks. To see this, note that we can decompose ξ_t and ϵ_t as[1]

$$\xi_t = \sum_{j=0}^{t} \underbrace{\mathbb{E}_j \xi_t - \mathbb{E}_{j-1}\xi_t}_{\xi_{t,j}} \qquad \text{and} \qquad \epsilon_t = \sum_{j=0}^{t} \underbrace{\mathbb{E}_j \epsilon_t - \mathbb{E}_{j-1}\epsilon_t}_{\epsilon_{t,j}}\ , \tag{S2}$$

where $\mathbb{E}_j(\cdot) = \mathbb{E}(\cdot|\mathcal{F}_j)$, with $\mathcal{F}_j$ the information set available at time j. The increment $\xi_{t,j} \equiv \mathbb{E}_j\xi_t - \mathbb{E}_{j-1}\xi_t$ is the component of ξ_t that is released at time $j \leq t$. In other words $\xi_{t,j}$ is a news shock released at $j \leq t$, and (S2) decomposes the shock ξ_t —a shock realized at time t— as a sum of news shocks $\xi_{t,j}$ revealed all the way until time t with $\xi_t = \sum_{j=0}^{t} \xi_{t,j}$. Similarly for $\epsilon_{t,j}$. By construction the news shocks are serially uncorrelated.

Thus, to identify the impulse responses in (S1), we require observing proxies for the news shocks in $\boldsymbol{\xi}_0 = (\xi_{0,0}, \xi_{1,0}, \xi_{2,0}, \ldots)'$ and $\boldsymbol{\epsilon}_0 = (\epsilon_{0,0}, \epsilon_{1,0}, \epsilon_{2,0}, \ldots)'$.

For exposition purposes we dropped the zero subscript and worked under perfect foresight.

S2 Implementation guide

An attractive feature of the ORA and DML statistics is that they can be readily computed from standard econometric methods. The sufficient statistics underlying the statistics — impulse responses to structural shocks— are well studied, and we can draw on a large macro-econometric literature precisely devoted to the estimation of these statistics, from the identification of structural shocks (e.g., Ramey, 2016) to the estimation of impulse responses (e.g., Li, Plagborg-Møller and Wolf, 2024).

To make this clear, consider the equilibrium representation under some rule ϕ

$$\mathbf{Y} = \Gamma_b\boldsymbol{\Xi}_b + \Gamma_{-b}\boldsymbol{\Xi}_{-b} + \mathcal{R}_a\boldsymbol{\epsilon}_a + \mathcal{R}_{-a}\boldsymbol{\epsilon}_{-a}\ ,$$

[1] As is common in the optimal policy literature, we impose $\mathbb{E}_{-1}\xi_t = 0$ and $\mathbb{E}_{-1}\epsilon_t = 0$, for all $t = 0, 1, \ldots$. Alternatively, one could let the sums run from $-\infty$ until t.

where the entries of $\mathcal{R}_a$ and Γ_b are the coefficients corresponding to the projection of the variables $\mathbf{Y}$ on the subset shocks $\boldsymbol{\epsilon}_a$ or $\boldsymbol{\Xi}_b$. For convenience we assume that the researcher is interested in a finite number of variables such that $\mathcal{W}$ has a finite number of non-zero diagonal elements and we let $\mathbf{Y}^w$ be the finite collection of selected elements of $\mathcal{W}^{1/2}\mathbf{Y}$. Further, let $\mathcal{R}_a^w$ and Γ_b^w denote the subset causal effects corresponding to the selected rows of $\mathcal{W}^{1/2}\mathcal{R}_a$ and $\mathcal{W}^{1/2}\Gamma_b$.

To compute the subset impulse responses we rely on a sample of realizations of the outcome variables $\mathbf{Y}^w$ during the policy makers term, i.e. $\{\mathbf{Y}_t^w, t = t_s, \ldots, t_e\}$ with t_s the starting period and t_e the ending period. The subset causal effects can be estimated by considering

$$\mathbf{Y}_t^w = \Gamma_b^w \boldsymbol{\Xi}_{b,t} + \mathcal{R}_a^w \boldsymbol{\epsilon}_{a,t} + \mathbf{V}_t^w \ , \qquad t = t_s, \ldots, t_e, \tag{S3}$$

where $\boldsymbol{\Xi}_{b,t}$ and $\boldsymbol{\epsilon}_{a,t}$ are the subset of news shocks that are realized at time t and $\mathbf{V}_t^w$ includes all other structural shocks, both policy and non-policy inputs that are not included in the selections a and b, respectively, as well as initial conditions and future errors.

We can recognize (S3) as a system of stacked local projections (Jordà, 2005). This implies that given (i) an appropriate identification strategy and (ii) an accompanying estimation method, we can estimate the impulse responses $\mathcal{R}_a^w$ and Γ_b^w using standard local projection methods. Any identification strategy — short run, long run, sign, external instruments, etc — can be used, based on which an appropriate estimation method — OLS or IV, with or without shrinkage, etc — can be selected, see Ramey (2016) and Stock and Watson (2018) for different options. Moreover, we recall from Plagborg-Møller and Wolf (2021) that in population local projections and structural VARs estimate the same impulse responses; therefore all SVAR methods discussed in Kilian and Lütkepohl (2017), for instance, can also be adopted for estimating the impulse responses Γ_b^w and $\mathcal{R}_a^w$. Given such estimates we compute the ORA noting that

$$\mathcal{T}^*_{\xi,ab} = -(\mathcal{R}_a'\mathcal{W}\mathcal{R}_a)^{-1}\mathcal{R}_a'\mathcal{W}\Gamma_b = -(\mathcal{R}_a^{w\prime}\mathcal{R}_a^w)^{-1}\mathcal{R}_a^{w\prime}\Gamma_b^w$$

and the DMLs

$$\Delta_{\xi,ab} = \mathrm{Tr}(\Gamma_b'\mathcal{W}\mathcal{R}_a(\mathcal{R}_a'\mathcal{W}\mathcal{R}_a)^{-1}\mathcal{R}_a'\mathcal{W}\Gamma_b) = \mathrm{Tr}(\Gamma_b^{w\prime}\mathcal{R}_a^w(\mathcal{R}_a^{w\prime}\mathcal{R}_a^w)^{-1}\mathcal{R}_a^{w\prime}\Gamma_b^w),$$

and

$$\Delta_{\epsilon,aa} = \mathrm{Tr}(\mathcal{R}_a'\mathcal{W}\mathcal{R}_a) = \mathrm{Tr}(\mathcal{R}_a^{w\prime}\mathcal{R}_a^w) \ .$$

Here we will not discuss any specific approach but instead directly postulate that the researcher is able to obtain estimates, say $\widehat{\mathcal{R}}_a^w$ and $\widehat{\Gamma}_b^w$, of which the distribution can be approximated by

$$\text{vec}\left(\begin{bmatrix}\widehat{\mathcal{R}}^w_a\\ \widehat{\Gamma}^w_b\end{bmatrix}-\begin{bmatrix}\mathcal{R}^w_a\\ \Gamma^w_b\end{bmatrix}\right)\overset{a}{\sim} F\ ,$$

where F is some known distribution function that can be estimated consistently by $\widehat{F}$. Such approximation can be obtained for many impulse response estimators using either frequentist (asymptotic and bootstrap) or Bayesian methods.

Using the approximating distribution $\widehat{F}$, we can simulate draws for $\mathcal{R}^w_a$ and Γ^w_b, and compute $\mathcal{T}^*_{\xi,ab}$, $\Delta_{\xi,ab}$ and $\Delta_{\epsilon,ab}$ for each draw. Given the sequence of draws we can construct a confidence set for each statistic, or any of its individual entries at any desired level of confidence. We note that if the distribution F is normal we can use the delta method to analytically compute the distributions, but we generally recommend using bootstrap or Bayesian methods.

Further, we briefly comment on how to estimate $\mathcal{E}^0_{ab}=\mathcal{L}^0-\mathcal{L}^0_{ab}$. First, the realized loss gives an estimate of $\mathcal{L}^0=\mathbb{E}(\mathbf{Y}'\mathcal{W}\mathbf{Y})$ computed under ϕ^0. To see that, let $\mathbf{Y}^w_t$ denote the vector of selected elements of $\mathcal{W}^{1/2}\mathbf{Y}_t$, where $\mathbf{Y}_t$ is the time t realization of $\mathbf{Y}$. Suppose that the evaluation period is from $t=1,\ldots,n$, then $\frac{1}{n}\sum_{t=1}^n \mathbf{Y}^{w\prime}_t\mathbf{Y}^w_t$ provides an estimate for $\mathcal{L}^0$. Second, $\mathcal{L}^0_{ab}$ can be measured from the sufficient statistics, see Proposition 2.

S3 Additional empirical results

We describe three robustness exercises: (i) identification of monetary shocks, (ii) alternative monetary periods, and (iii) dynamic shock heterogeneity across periods.

Identification of monetary shocks

First, we consider robustness to the identification of monetary shocks, and table S1 shows the ORA statistics estimated using sign-identified monetary policy shocks. The results are remarkably consistent with our baseline estimates, with ORAs generally of similar magnitudes and same levels of statistical significance.[2]

Alternative monetary periods

Second, we consider robustness to the definition of the monetary period. Table S2 display ORA estimated for alternative definition of the monetary regime: (i) the Gold Standard

[2] As a third alternative identification of monetary shocks, we identified monetary shocks using short run restrictions (e.g. Sims, 1980). The results were also similar.

period over 1879-1932,[3], (ii) the interwar period after the US went off the Gold Standard in 1933, (iii) the Bretton Woods system (1946-1971), (iv) the post Bretton Woods period until the beginning of the Great Moderation (1971-1984), and (v) a pre Volcker period (1951-1979).

Overall the results confirm our main finding with no uniform improvements in performance until 1984, poor (i.e., too passive) reaction to bank panics during the Gold Standard (passive or active) period, and similarly poor (i.e., too passive) reaction to supply-side shocks in the post WWII period. We also note an interesting and novel result: the ORA for government spending is significantly negative for the Bretton Woods period (1946-1971). Since the government spending shocks of the 1960s were mostly positive (capturing two large government programs related to US space program in the early 60s and the Vietnam war in the second half of the 60s), our estimated ORA implies that the Fed did not raise the policy rate enough in the face of these large government programs, confirming earlier narrative evidence of a too soft reaction of William Martin's Fed during that period Romer and Romer (2004); Hack, Istrefi and Meier (2023).

Last, this robustness exercise also highlights a trade-off inherent to our sufficient statistics approach. Our method requires large enough samples and/or samples with sufficiently large shocks in order to estimate the impulse responses with enough confidence. The interwar period for instance is a very short sample, and all the ORAs are consequently estimated with large error bands. This does not invalidate the approach, but it makes it inference more difficult. Similarly for the Bretton Woods period; there were no major energy price shocks during that period, making the ORA uncertain.

Dynamic shock heterogeneity across periods

In a dynamic setting the policy maker has to set the entire path of her policy instruments to offset the entire path of non-policy news shocks. A subset ab will only probe the optimality of the policy at the specific horizons captured by the news shocks in a and b,[4] but we can probe the sensitivity of the results to "missing horizons" in the subsets $\boldsymbol{\epsilon}_a$ and $\boldsymbol{\Xi}_b$ by considering a higher level of time aggregation.

Based on time aggregated paths we obtain impulses responses for averages and we can compute the ORA and DML corresponding to time aggregated loss function, and thereby evaluate policy maker exactly as in the main text but at a coarser time dimension. The benefit is that time aggregation mutes the problem of missing horizons: In the limit where

[3]In the baseline specification, we treated the Early Fed period as different from the Gold Standard, as the Fed had considerably leeway in varying its god cover ratio. That said, the extent to which the Gold Standard limited Fed monetary policy remains a debated question (e.g., Eichengreen, 1992; Hsieh and Romer, 2006).

[4]For instance, if the subset ϵ_a only features short-horizon policy shocks, then the subset-based evaluation will only informative about how well policy makers used the policy path at short horizons.

the time unit step becomes the entire period of evaluation,[5] the distance Δ_{ab} captures to the total distance to minimum loss Δ_b as the policy problem becomes static (as in Section 2), and the subset policy evaluation becomes exhaustive for the identified non-policy shocks.[6]

In our empirical work we consider robustness to possible dynamic shock heterogeneity across periods. Specifically, Table S3 reports the ORA statistics estimated for a higher level of time aggregation, with impulse responses averaged over 3-year window. The results are very similar to our baseline results, indicating that dynamic shock heterogeneity appears to be a minor concern for our Fed comparison across periods.

S4 Large gold discoveries and extraction maxima

In this section, we describe how we constructed our instrumental variable for movements in the monetary base under the passive Gold Standard of 1879-1912.

Under a Gold Standard, the monetary base depends on the amount of gold in circulation, which can itself vary for exogenous reasons related to the random nature of gold discoveries or development of new extraction techniques (e.g., Barsky and De Long, 1991). As such, we use large gold mine discoveries (the dates of discoveries that led to gold rushes) and mine peak extraction (the dates when these large mines reached peak production) to create an instrument variable for movements in the monetary base. Given the historical difficulty in predicting the amount of gold available in any given region (either at the onset of a gold rush or at its zenith), we can consider these events as unanticipated and unrelated to the state of the business cycle.

To inform our narrative identification, we rely on Koschmann and Bergendahl (1968), which is a detailed account of Gold production districts in the US since 1799. Figures S1–S4 show gold production in four states that experienced large gold rushes. In each case, the gold rush led to large variations in gold production; in the order of 30-40 percent of *national* production.

Figure S5 plots national gold production along with our identified dates for the discoveries of large mines. We also report peak extraction dates when the date could be unambigiously identified from the narrative accounts. The large discovery and peak extraction dates are the Sutter's Mill discovery in California, the Comstock lode mine discovery in Nevada, the Comstock lode maximum (1877-Q1), the Cripple Creek discovery in Colorado (1891-Q3), the

[5]This is the route followed by Blinder and Watson (2016), who evaluate US presidents from average realizations over the entire policy makers' tenure.

[6]In addition, one could exploit the recent "VAR-plus" approach proposed by Caravello, McKay and Wolf (2024) and make structural assumptions on the transmission of shocks in order to complement the subset shock evidence. Alternatively, one could impose an invertibility assumption on a large scale VAR in order to span the entire set of shocks affecting policy makers (Caravello, McKay and Wolf, 2024). This is left for future research.

Bonanza creek discovery in Alaska (1896-Q3), the Goldfield discovery in Nevada in (1902-Q1), the Goldfield maximum in Nevada (1910-Q1) and the Juneau maximum in Alaska. Since our passive Gold Standard period covers 1879-1912, we only use the dates above that are explicitly spelled in parentheses.

We code the Gold shocks as one when a new mine was discovered and minus one when the peak was reached.

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Table S1: ORA statistics, sign-based identification

Non-policy shock Shock sign convention	Bank panics $u\uparrow$	G $u\uparrow$	Energy $\pi\uparrow$	π^e $\pi\uparrow$	TFP $\pi\uparrow$
Pre Fed 1879−1912	**−0.6*** (−0.9,−0.3)	**−0.4*** (−0.7,−0.2)	**0.0** (−0.4,0.4)	—	**0.3*** (0.1,0.6)
Early Fed 1913−1941	**−0.8*** (−1.2,−0.4)	**−0.4*** (−0.7,0)	**0.0** (−0.3,0.3)	**0.7*** (0.4,1.1)	**0.0** (−0.4,0.3)
Post WWII 1951−1984	—	**−0.3** (−0.6,0.1)	**0.5** (−0.1,1.1)	**0.7*** (0.3,1.1)	**0.5*** (0.0,1.0)
Post Volcker 1990−2019	**−0.3*** (−0.7,0.0)	**0.3** (−0.2,0.8)	**−0.3** (−0.8,0.3)	**0.2** (−0.2,0.5)	**0.2** (−0.1,0.5)

Median ORA statistics together with 68% credible sets. The monetary policy shocks are identified using sign restrictions as described in main text. The financial shocks are bank panics from Reinhart and Rogoff (2009), the government spending shocks (G) are from Ramey and Zubairy (2018), TFP shocks from Gali (1999), energy shocks are computed using the peak-over-threshold approach of Hamilton (1996), and inflation expectation shocks (π^e) are innovations to inflation expectations as measured from Cecchetti (1992) for Early Fed period and from the Livingston survey after 1946. For the Pre Fed period the TFP, G and Energy ORAs are computed over the 1890-1912 period.

Table S2: ORA statistics, Alternative regime definition

Non-policy shock Shock sign convention	Bank panics $u\uparrow$	G $u\uparrow$	Energy $\pi\uparrow$	π^e $\pi\uparrow$	TFP $\pi\uparrow$
Gold Standard 1879−1932	**−0.9*** (−1.2,−0.6)	**−0.3*** (−0.6,−0.1)	**−0.1** (−0.4,0.2)	**0.8** (−0.8,1.6)	**0.1** (−0.1,0.4)
Interwar, off Gold 1933−1941	—	**−1.1** (−3.7,3.3)	**−0.1** (−0.9,0.7)	**0.3** (−0.4,1)	**−0.5** (−1.2,0.2)
Bretton Woods 1946−1971	—	**−0.6*** (−0.9,−0.2)	**−0.2** (−0.8,0.4)	**0.3** (−0.3,0.8)	**0.4** (−0.1,0.8)
Post Bretton Woods 1971−1984	—	**0.0** (−0.5,0.6)	**0.7** (−0.2,1.3)	**0.8*** (0.0,1.2)	**0.6** (−0.1,1.2)
Pre Volcker 1951−1979	—	**−0.4*** (−0.7,0.0)	**0.2** (−0.4,0.7)	**0.6*** (0.0,1.0)	**0.3** (−0.2,0.9)

Median ORA statistics together with 68% credible sets. The monetary policy shocks are identified using sign restrictions as described in main text. The financial shocks are bank panics from Reinhart and Rogoff (2009), the government spending shocks (G) are from Ramey and Zubairy (2018), TFP shocks from Gali (1999), energy shocks are computed using the peak-over-threshold approach of Hamilton (1996), and inflation expectation shocks (π^e) are innovations to inflation expectations as measured from Cecchetti (1992) for Early Fed period and from the Livingston survey after 1946. For the Pre Fed period the TFP, G and Energy ORAs are computed over the 1890-1912 period.

Table S3: ORA statistics, lower frequency

Non-policy shock Shock sign convention	Bank panics $u\uparrow$	G $u\uparrow$	Energy $\pi\uparrow$	π^e $\pi\uparrow$	TFP $\pi\uparrow$	Average |ORA|
Pre Fed 1879−1912	**−1.1*** (−2.3,−0.3)	**−1.2*** (−2.5,−0.1)	**0.0** (−0.8,0.7)	—	**0.8** (−0.6,1.9)	**0.6**
Early Fed 1913−1941	**−1.4*** (−2.3,−1.0)	**−0.6*** (−1.1,−0.2)	**0.1** (−0.2,0.5)	**0.7*** (0.4,1.1)	**0.1** (−0.3,0.6)	**0.5**
Post WWII 1951−1984	—	**−0.2** (−0.8,0.4)	**0.9*** (0.2,1.5)	**1.3*** (0.6,2.1)	**0.7** (−0.1,1.4)	**0.7**
Post Volcker 1990−2019	**−0.3** (−0.8,0.2)	**0.1** (−0.5,0.6)	**−0.2** (−0.9,0.7)	**0.0** (−0.4,0.3)	**−0.3** (−0.7,0.1)	**0.2**

Median ORA statistics together with 68% credible sets computed from impulse responses averaged over 3-year windows. See Table II for shock identification assumptions.

Figure S1: Alaska Gold Production

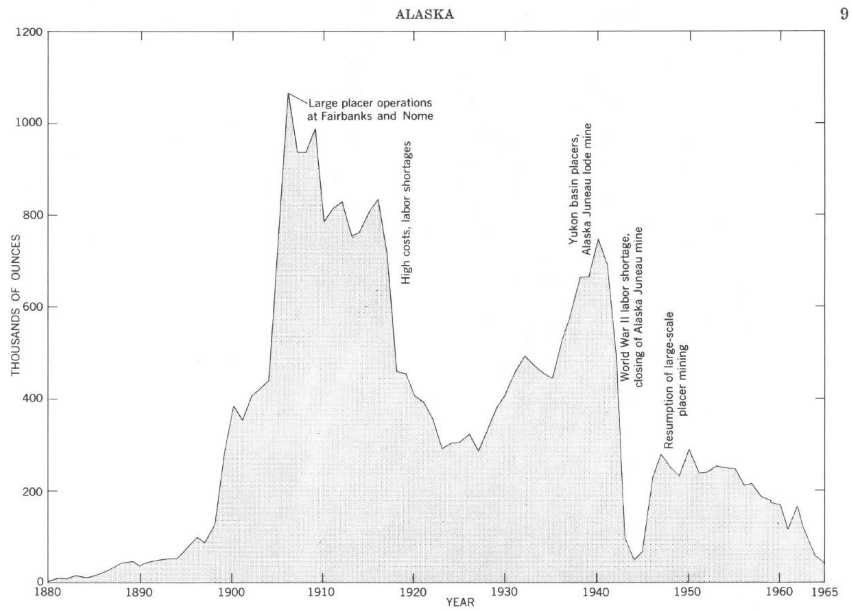
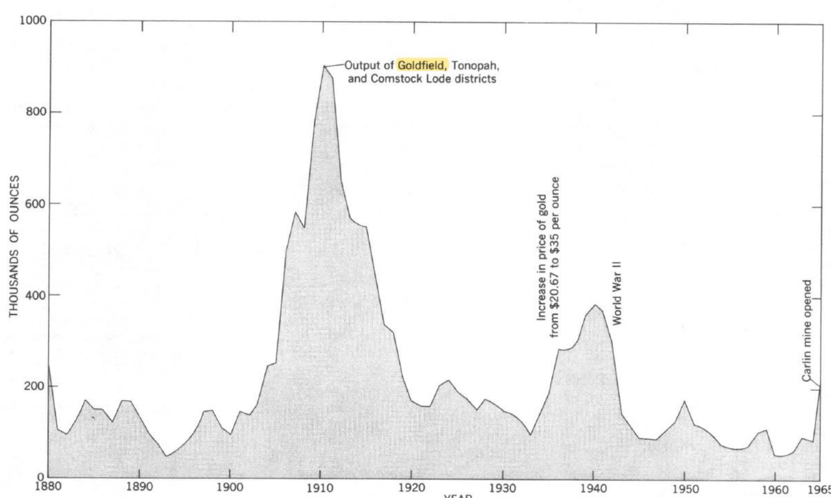


FIGURE 4.—Annual gold production of Alaska, 1880–1965. Sources of data: 1880–1900, U.S. Geological Survey (1883–1924); 1900–42, Smith (1944, p. 6); 1943–59, U.S. Bureau of Mines (1933–66). Production reported in dollar value was converted to ounces at prevailing price per ounce.

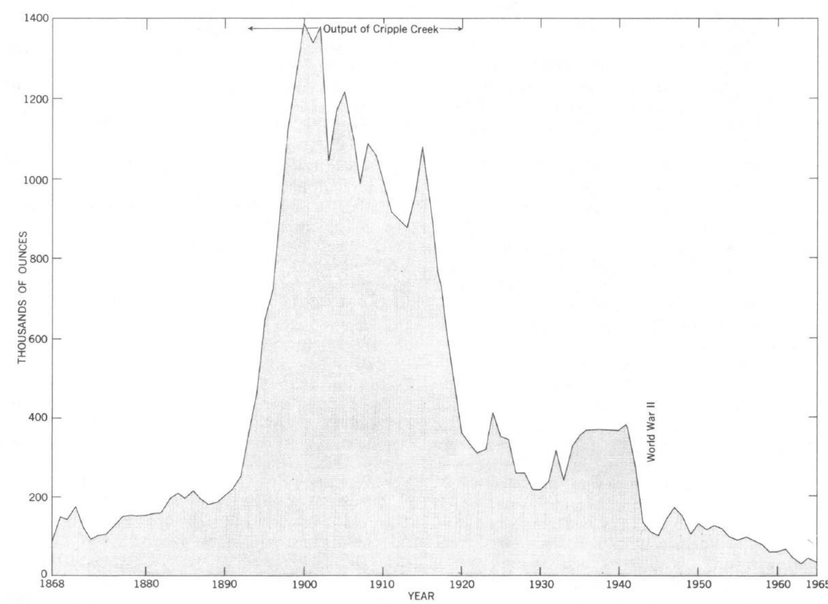
Source: Koschmann and Bergendahl (1968).

Figure S2: Nevada Gold Production



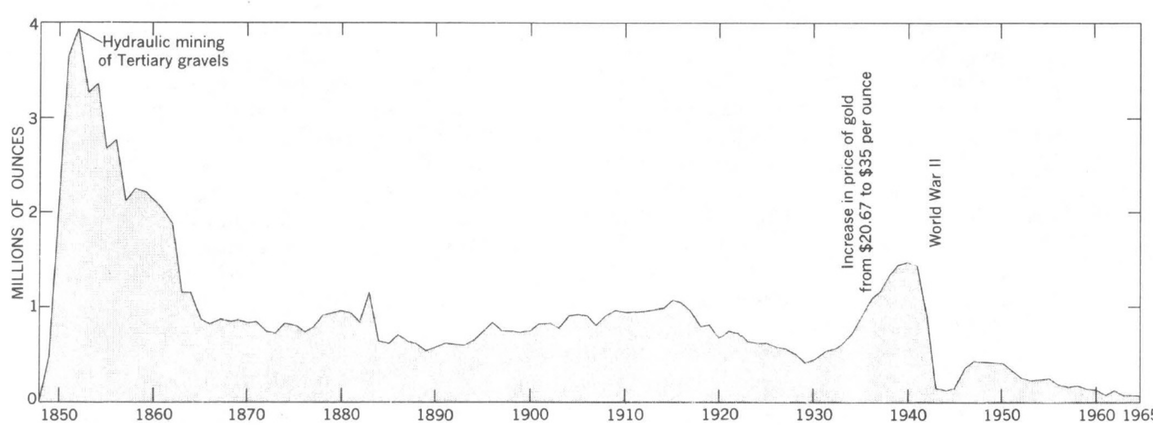
Source: Koschmann and Bergendahl (1968).

Figure S3: Colorado Gold Production



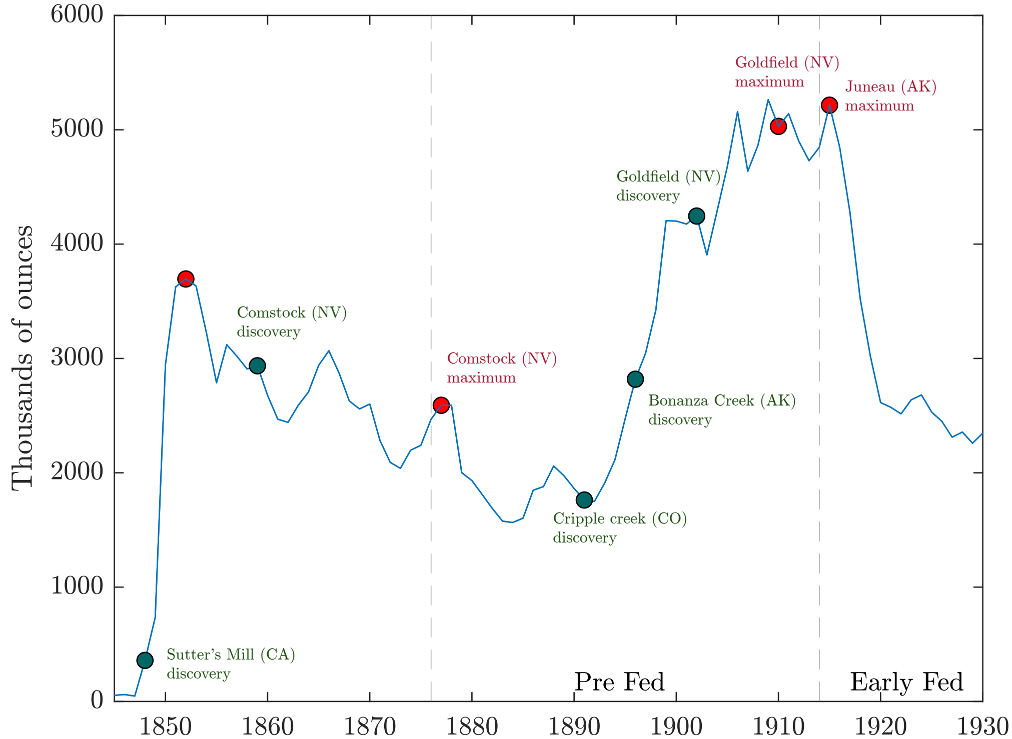
Source: Koschmann and Bergendahl (1968).

Figure S4: California Gold Production



Source: Koschmann and Bergendahl (1968).

Figure S5: US Gold Production, 1845–1930



US gold production in thousands of ounces. The green dots correspond to large mine discoveries and the red dots correspond to peak extractions.